UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Modelo y desarrollo de un sistema de gestión óptima para una microrred empleando algoritmos bio-inspirados

Model and development of an optimal management system for a microgrid using bio-inspired algorithms

TESIS DOCTORAL

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Dedicado a mi querida madre, que sin su amor y paciencia nada de esto hubiera sido posible; y a mis hermanas Marienne, que siempre vivirá en mi corazón y memoria; y Mónica que siempre está dispuesta a ayudar a quien lo necesita.

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ANN	Redes neuronales artificiales
CENER	Centro Nacional de Energías Renovables
ER	Energía Renovable
FV	Fotovoltaico
GC	Generación centralizada
GD	Generación distribuida
GEI	Gases de efecto invernadero
GWO	Grey Wolf Optimizer
IEA	Agencia Internacional de la Energía / International Energy Agency
INC	Incremental Conductance
JCR	Journal Citation Reports
LabDER	Laboratorio de Energías Renovables
MPPT	Maximum Power Point Tracking Controller
MSD	Mean Standard Deviation
PID	Proportional-Integral-Derivative
PO	Perturb and Observe
PSO	Particle Swarm Optimization
RNA	Redes Neuronales Artificiales
RMSE	Root Mean Squared Error
SA	Simulated Annealing
SJR	Scimago Journal & Country Rank / Science Journal Rankings
SR	Sistema de Red
SGE	Sistema de Gestión de la Energía
UPV	Universitat Politècnica de València
WOA	Whale Optimization Algorithm
SOS	Symbiotic Organism Search algorithm

Resumen

Las fuentes de energía renovable (ER) permiten una alta disgregación, por lo que hacen posible generar la energía que se utilizará en el mismo sitio de su aprovechamiento. Esto favorece un cambio en la estructura de las redes eléctricas, permitiendo pasar de un esquema de generación centralizado a un esquema distribuido. Sin embargo, las fuentes de ER son altamente dependientes de las condiciones medioambientales como la radiación solar, la nubosidad, el viento, entre otros, por lo que lograr un sistema de generación basado en energías renovables es un reto en la actualidad. Los sistemas de generación que integran fuentes renovables tienen que ser capaces de establecer estrategias de control y gestión de la energía que para hacer un uso eficiente de ella e intentar cubrir la demanda de energía de forma óptima al combinar más de un tipo de fuente y sistema de almacenamiento, siendo posible operar de manera aislada o conectada a la red eléctrica. En la actualidad es de interés el estudio, desarrollo e implementación de sistemas gestores de la energía (SGE) para microrredes eléctricas híbridas, que permitan aumentar su eficiencia, fiabilidad, y disminuir los costes de instalación, operación y mantenimiento. Diversos estudios de investigación han probado múltiples estrategias, desde SGE basados en reglas, algoritmos comparativos, controladores clásicos, y en años recientes, la integración de algoritmos de optimización bio-inspirados e inteligencia artificial. Estos algoritmos han mostrado ser una alternativa interesante a las técnicas clásicas para la solución de problemas de optimización y control en diversos problemas de ingeniería, su aplicación en el ámbito de las microrredes sigue en estudio y en ello se basa este trabajo de investigación. Los algoritmos bio-inspirados se fundamentan en imitar matemáticamente los mecanismos y estrategias que la naturaleza ha implementado a lo largo de millones de años para lograr un equilibrio en su funcionamiento, por ejemplo, imitando el cómo las aves vuelan en parvada buscando alimento, o como las hormigas y los lobos siguen patrones para la búsqueda de su alimento, o como las especies llevan a cabo mecanismos de cruce con el objetivo de mejorar su raza haciéndolas una especie optimizada y mejorando su supervivencia. Por tanto, se puede hacer una analogía con los sistemas artificiales para la mejora de controladores y diseño de sistemas en microrredes eléctricas.

En este trabajo de investigación se muestra el modelo y desarrollo de un sistema de gestión óptima para una microrred empleando algoritmos bio-inspirados con el objetivo de mejorar su desempeño, partiendo desde el control primario, con la mejora de los convertidores de potencia, hasta el control terciario con las transacciones energéticas de la microrred. Se exploran diversos algoritmos, evaluando su desempeño. Los resultados para las diferentes etapas de esta investigación se encuentran plasmados en cuatro diferentes publicaciones científicas que se detallan en el Capítulo 2 del presente documento, donde se explica la metodología y los principales resultados y hallazgos para cada una de ellas.

Resum

Les fonts d'energia renovables (ER) permeten una alta desagregació, pel que fan possible generar l'energia que s'utilitzarà en el mateix lloc del seu aprofitament. Això afavoreix un canvi en l'estructura de les xarxes elèctriques, permetent passar d'un esquema de generació centralitzat a un esquema distribuït. No obstant, les fonts d'ER són altament dependents de les condicions mediambientals com la radiació solar, la nuvolositat, el vent, entre altres; pel que aconseguir un sistema de generació basat en energies renovables és un repte. Els sistemes de generació que integren energies renovables han de ser capaços de: establir estratègies de control i gestió de l'energia que es genera per fer un ús eficient d'ella i intentar cobrir la demanda d'energia de la millor manera possible al combinar més d'un tipus de font d'energia, i sistemes d'emmagatzemament. Aquest esquema es coneix com a microxarxa elèctrica, la qual és capaç d'operar de manera aïllada de la xarxa elèctrica principal, o de manera interconnectada.

Actualment s'està interessant en l'estudi, desenvolupament i implementació de sistemes gestors de l'energia (SGE) per a microxarxes elèctriques híbrides, que permeten augmentar la seua eficiència, fiabilitat i reduir els costos de la seua instal·lació i d'operació i manteniment. S'han provat múltiples estratègies, des de SGE basats en regles, algorismes comparatius, controladors clàssics i, en anys recents, la integració d'algorismes d'optimització bio-inspirats i intel·ligència artificial. Aquests algorismes han demostrat ser una alternativa interessant a les tècniques clàssiques per a la solució de problemes d'optimització i control en diversos problemes d'enginyeria, la seua aplicació en l'àmbit de les microxarxes continua en estudi. Els algorismes bio-inspirats es basen en imitar matemàticament els mecanismes i estratègies que la Natura ha implementat al llarg de milions d'anys per aconseguir equilibri en el seu funcionament, per exemple, imitant com les aus volen en ramat buscant menjar, o com les formigues i els llops segueixen patrons per a la recerca del seu menjar, o com les espècies porten a terme mecanismes de creuament amb mira a millorar la seua raça fent-les una espècie més apta per a la supervivència;, el qual es pot fer una analogia a sistemes artificials per a la millora de controladors i disseny de sistemes en microxarxes elèctriques.

En aquest treball de recerca es mostra el model i desenvolupament d'un sistema de gestió òptima per a una microxarxa emprant algorismes bio-inspirats amb l'objectiu de millorar el seu rendiment, partint des del control primari, amb la millora dels convertidors de potència, fins al control terciari amb les transaccions energètiques de la microxarxa. S'exploren diversos algorismes, avaluant el seu rendiment. Els resultats per a les diferents etapes d'aquesta recerca es troben plasmats en quatre diferents publicacions científiques que es detallen al Capítol 2 del present document, on s'explica la metodologia i els principals resultats i troballes per a cada una d'elles.

Abstract

Renewable energy sources (RES) allow for high disaggregation, making it possible to generate energy at the site of its use. This favors a change in the structure of electrical grids, allowing for a transition from a centralized generation scheme to a distributed scheme. However, RES are highly dependent on environmental conditions such as solar radiation, cloudiness, wind, among others, making the creation of a renewable energy generation system a challenge. Generation systems that integrate renewable energies must be able to establish control and energy management strategies to make efficient use of the energy generated and try to meet the energy demand in the best possible way by combining more than one type of energy source and storage systems. This scheme is known as a microgrid, which is capable of operating independently from the main electrical grid or interconnecting with it.

Currently, the study, development, and implementation of energy management systems (EMS) for hybrid microgrids are of interest in order to increase their efficiency, reliability, and reduce installation, operation, and maintenance costs. Multiple strategies have been tested, including rule-based EMS, comparative algorithms, classical controllers, and in recent years, the integration of bio-inspired optimization algorithms and artificial intelligence. These algorithms have shown to be an interesting alternative to classical techniques for solving optimization and control problems in various engineering problems, although their application in the field of microgrids is still under study. Bio-inspired algorithms are based on mathematically imitating the mechanisms and strategies that Nature has implemented over millions of years to achieve balance in its operation, for example, by imitating how birds fly in flocks in search of food, or how ants and wolves follow patterns to search for food, or how species carry out crossing mechanisms in order to improve their breed and make them more suitable for survival; in other words, they are based on how Nature optimizes its resources to prosper. Therefore, an analogy can be made with artificial systems for improving controllers and designing systems in microgrids.

In this research work, the model and development of an optimal management system for a microgrid using bio-inspired algorithms is presented with the aim of improving its performance, starting from primary control, with the improvement of power converters, to tertiary control with the energy transactions of the microgrid. Various algorithms are explored, evaluating their performance. The results for the different stages of this research are reflected in four different scientific publications that are detailed in Chapter 2 of this document, where the methodology and main results and findings for each of them are explained.

Estructura

El documento está estructurado en cuatro capítulos. En el capítulo 1, empieza con una introducción donde se presentan los antecedentes y contexto global, objetivos y metodología del presente trabajo. El compendio de artículos científicos se incluye a lo largo del Capítulo 2, y, finalmente, en el Capítulo 3 se muestran las principales conclusiones y trabajo futuro de esta investigación. La Tabla 1 muestra la organización general del presente trabajo.

Tabla 1 Estructura del documento de tesis.

Capítulo	**Apartado**
Capítulo 1. Introducción	Antecedentes. Objetivos. Metodología. Estructura. Referencias.
Capítulo 2. Publicaciones científicas	Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller. Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms. Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach. A multi microgrid energy management model implementing an evolutionary game-theoretic approach.
Capítulo 3. Conclusiones y trabajo futuro	Conclusiones. Trabajo futuro.
Capítulo 4. Otras publicaciones y actividades	Publicaciones de congreso Participaciones en congreso Ponencias Talleres/Cursos Estancias

Capítulo 1.

Introducción

1.1 Introducción

El presente trabajo constituye una tesis doctoral en su modalidad por compendio de artículos científicos. Se presentan los principales resultados y hallazgos de tres años de investigación plasmados en cuatro artículos científicos, publicados en prestigiosas revistas indexadas en el Journal Citation Report (JCR) y el Scimago Journal & Country Rank (SJR), los cuales tratan sobre diferentes aspectos de técnicas modernas de control y gestión de microrredes eléctricas integrando algoritmos bio-inspirados de optimización para la mejora de su eficiencia. En el ámbito científico, una de las principales aportaciones del presente trabajo de investigación es el haber integrado desde las etapas de control primario, secundario y terciario algoritmos bio-inspirados, con el objeto de aumentar la eficiencia de los sistemas híbridos de generación.

Las microrredes eléctricas basadas en ER al combinar diversas fuentes de generación, y almacenamiento en su caso, requieren de un SGE eficiente capaz de actuar en todos los niveles de la microrred para asegurar un funcionamiento eficiente la misma. En cuanto a gestión y control de la energía, este se divide en tres principales niveles: primario, secundario y terciario. Esta investigación aborda de manera novedosa el problema de control y gestión de la energía en las microrredes al incorporar algoritmos bio-inspirados en todos los niveles de control. En el nivel primario, se han implementado mejoras en el diseño de los controladores de los convertidores de potencia, de esta manera, se logra un control a nivel primario descentralizado, como se muestra y detalla en la publicación "**Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller**", el objetivo principal de este artículo fue realizar una exploración sobre el desempeño de tres algoritmos bio-inspirados en comparación de técnicas clásicas para la sintonización de controladores en convertidores de potencia; dentro de los resultados mostrados en este artículo destaca la comparativa en tiempo de cómputo para la sintonización de un controlador PID para un Boost Converter, donde el algoritmo de Grey Wolf Optimizer (GWO) tuvo el mejor desempeño siendo un 64% más veloz que el algoritmo Particle Swarm Optimization (PSO) pero un 9 más lento que el Genetic Algorithm (GA), sin embargo, con un RMSE menor en 49% y 48% en comparación con el RMSE obtenido por el PSO y GA respectivamente, además de converger a partir de la tercera iteración en el mejor resultado, a diferencia del PSO y GA que lo hacen a partir de la novena iteración. Estas características del GWO en comparación con los otros dos algoritmos hacen que el controlador tenga una respuesta más rápida y con menos oscilaciones ante variaciones en la tensión de alimentación y en la carga conectada al convertidor. Como segunda etapa de esta investigación en el control primario, se trabajó en la integración de un boost converter hacia un panel solar fotovoltaico con el objetivo de optimizar el Maximum Power Point Tracking Controller (MPPTC) utilizando algoritmos bio-inspirados en operación bajo condiciones lo más cercanas a la realidad, al considerar fluctuaciones de tensión a la salida del arreglo fotovoltaico debido a la variación de irradiación solar a lo largo del día y a las condiciones de nubosidad y sombreado repentido, así como una curva de consumo real. Para esta etapa se utilizaron datos de medición reales sobre irradiación y niveles de tensión, así como el modelado del sistema solar fotovoltaico de las instalaciones del Laboratorio de Recursos Energéticos Distribuidos (LabDER) de la Universitat Politècnica de València (UPV). Los principales resultados de esta segunda etapa del control primario se plasman en el artículo científico "**Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms**", en esta publicación, no solamente se comparan diferentes algoritmos bio-inspirados entre sí, sino que también se comparan diferentes tipos de controladores MPPT. Se muestra una comparativa entre un controlador MPPT discreto basado en PID optimizado por algoritmo GWO, PSO, Simulated Annealing (SA) y Whale Optimization Algorithm (WOA) contra los algoritmos para controlador MPPT de Incremental Conductance (INC) y de Perturb and Observe (PO). Los resultados muestran que el controlador optimizado por GWO logra extraer hasta un 6% más energía que cualquier otro controlador evaluado bajo las diferentes condiciones de simulación.

La etapa de control secundario y terciario está relacionada con los flujos de energía y la toma de decisiones del controlador central de la microrred bajo estudio. Para abordar el problema de control secundario y terciario se han implementado reglas de lógica difusa, algoritmos de optimización bio-inspirados y redes neuronales con lo que el sistema propuesto es capaz de hacer un uso óptimo de los recursos disponibles para cubrir la demanda de energía. Sobre el control de la energía dentro de una microrred, en el artículo "**Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach**" se realiza una extensión del método presentado en la publicación anterior, donde no solo se aplica ahora para un solo subsistema de generación la red neuronal optimizada, sino que se presenta una metodología de implementar más redes neuronales para el sistema híbrido de generación completo. En el trabajo presentado se muestra un modelo multicapa de redes neuronales artificiales optimizadas. En la primera capa la red neuronal estima la salida del arreglo solar FV a través de datos de entrada como irradiación solar, estación del año y hora; en la segunda capa de redes neuronales a través de mediciones del sistema de almacenamiento y la demanda de energía se hace una estimación de la demanda de energía al sistema gasificador, así como estimación de la evolución del estado de cargo del banco de baterías; finalmente, en la última capa de redes neuronales se predice la cantidad de biomasa requerida para cubrir la demanda de energía que no fue posible cubrir mediante las otras fuentes y el sistema de almacenamiento. Para cada etapa descrita anteriormente se realizaron entrenamientos para las redes neuronales optimizadas mediante PSO, y además, se muestra la metodología de selección de variables con base a un análisis de correlación previo y normalización de datos para la obtención de mejores resultados por parte de la redes neuronales. El desempeño del modelo propuesto para la gestión de la energía se evaluó en dos diferentes casos de estudios, donde se sometió el sistema a datos de entrada reales diferentes, los índices de desempeño fueron la raíz del error cuadrático medio (RMSE, root mean squared error) y la desviación estándar media (MSD, mean standard deviation); en promedio el RMSE fue de 0.1246 y el MSD de 0.4595 evaluando el sistema con datos experimentales contra datos simulados.

Finalmente, una vez realizado trabajo sobre control primario en las fuentes de generación y de gestión de la energía, en el artículo "**A multi-microgrid energy management model implementing an evolutionary game-theoretic approach**" se detalla una propuesta de modelo de gestión de la energía para una microrred en un entorno multi-microrred, en este modelo, a diferencia del pasado se hace extensión de la metodología para abarcar las transacciones de energía entre más de una microrred. En este trabajo se integra, además de los algoritmos de optimización y redes neuronales, también lógica difusa y conceptos de teoría de juegos para asegurar el máximo aprovechamiento de energías renovables. En este trabajo se consideran seis microrredes, con capacidad de intercambiar energía entre ellas según se requiera, el sistema es supervisado por un controlador central que a través de mediciones de variables medioambientales es capaz de determinar el modo de operación de cada microrred. El modelo de gestión de la energía multi microrred se basa en tres principales etapas. La primera etapa determina si el sistema opera en modo aislado o interconectado a la red; luego en la segunda etapa se lleva a cabo la gestión de la energía a través de la implementación de un sistema de lógica difusa que toma en cuenta el voltaje, el factor de potencia y la distorsión armónica total como indicadores de la calidad de la energía de cada microrred, y, se implementa también un algoritmo bio-inspirado basado en organismo simbiontes (SOS, Symbiotic Organism Search algorithm) combinado con el principio de Stackelberg de la teoría de juegos para determinar la microrred óptima para cubrir la demanda de energía; finalmente, a tercera etapa determina el nuevo estado de cada microrred mediante un modelo de cadena de Markov. Se realizó un análisis comparativo, en términos de potencia servida a la carga en cada microrred, potencia total generada e intercambio de energía entre las microrredes.

Esta tesis es resultado de más de tres años de investigación en los campos de microrredes eléctricas y algoritmos de optimización, por lo tanto, para cada etapa de la investigación se siguió una metodología específica. Si bien la tesis trata en general de algoritmos bio-inspirados de optimización integrados a diferentes modelos y etapas de control y gestión de las microrredes, no significa esto que se haya seguido un orden estricto entre control primario, secundario y terciario; esto debido a que las diferentes etapas de control pueden tratarse de manera independiente la una de la otra, y, de igual manera, la aplicación de los algoritmos de optimización. En el esquema de la Figura 1 se ilustran los hitos más representativos del desarrollo de la investigación llevada a cabo en este trabajo. La investigación ha sido un proceso continuo y riguroso que ha durado más de 3 años. La Figura 1 permite una visión general del progreso realizado desde la participación en congresos técnicos y de divulgación, estancias y publicación de artículos científicos en revistas de rigor científicos indexadas en el SJR y el JCR. Cabe destacar que en este documento de tesis no se han incluido todas las publicaciones generadas durante el doctorado puesto que con las incluidas en el capítulo 2 de esta tesis se cumple con los alcances propuestos al inicio de la investigación.

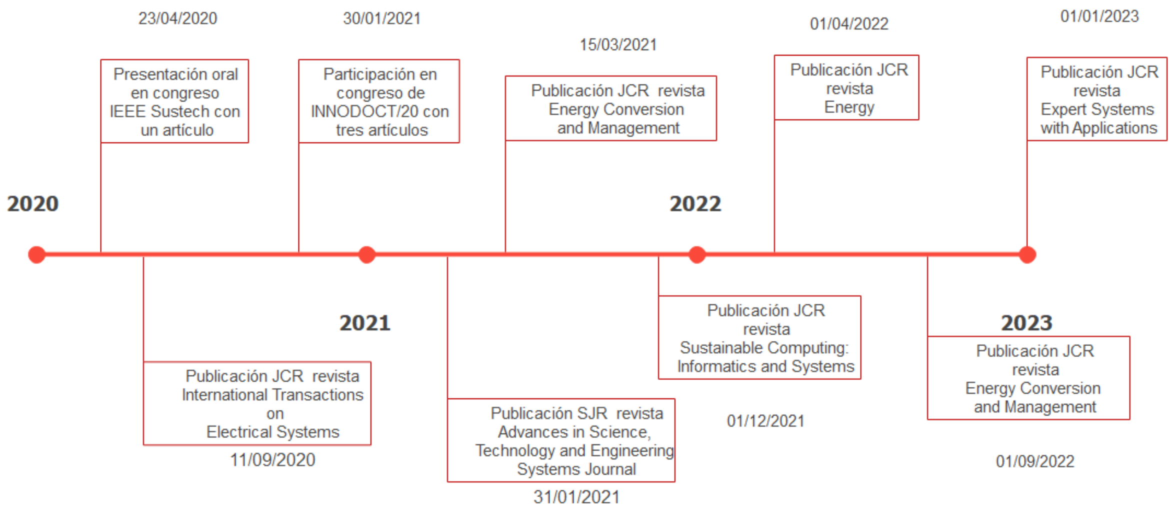

Figura 1 Línea temporal de hitos del desarrollo de la investigación presentada. Fuente: Elaboración propia.

Antecedentes

La creciente demanda energética a nivel global y la necesidad de reducir las emisiones de gases de efecto invernadero han impulsado la transición hacia un modelo energético más sostenible basado en fuentes de energía renovable. La energía renovable es aquella que se obtiene a partir de fuentes naturales que son inagotables o que se renuevan de forma natural, como la energía solar, eólica, hidráulica, geotérmica y de biomasa. Estas fuentes de energía renovable presentan numerosas ventajas en comparación con los combustibles fósiles, como la reducción de las emisiones de gases de efecto invernadero y otros contaminantes atmosféricos, la diversificación de la matriz energética, la seguridad energética y la creación de empleo. Sin embargo, a nivel mundial, es aún predominante la generación de energía a través de fuentes de origen fósil. En la Figura 2 se puede muestra la fracción global de las principales fuentes de energía en la actualidad.

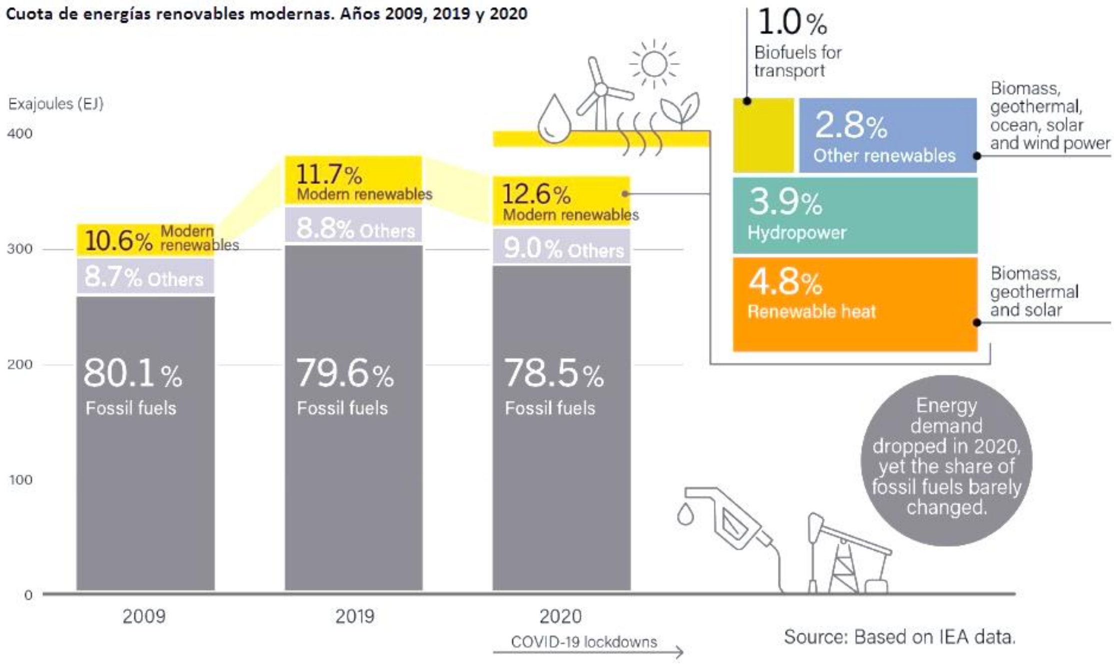

Figura 2 Origen primario de energía en los últimos años a nivel mundial. Fuente: https://www.iea.org/data-and-statistics.

La naturaleza dispersa de las fuentes renovables de energía hace que exista la posibilidad de pasar de un modelo centralizado de generación a uno distribuido, y más aún, híbrido. Cuando se incorpora más de un tipo de fuente de generación trabajando en conjunto y de manera local o cercana al sitio de aprovechamiento se habla del concepto de microrred eléctrica, que si esta incorpora técnicas avanzadas de monitoreo y tecnologías de la información se convierte en una microrred eléctrica inteligente [1], [2].

Al considerar las problemáticas anteriores que el esquema de generación centralizada presenta en el contexto global actual, es que, a partir de la integración de fuentes de energías renovables, surge el concepto de generación distribuida (GD), [3]. Como se mencionó con anterioridad, el crear microrredes eléctricas integrando fuentes de energía renovables tiene como característica que la energía suele generarse en el sitio de aprovechamiento, o muy cerca [4], esto hace que las pérdidas por transmisión y distribución se reduzcan, aumentando la eficiencia del sistema, reduciendo los fallos y, además, siendo amigable al medio ambiente al no utilizar fuentes de origen fósil como combustible primario [5].

La característica modular de la GD hace que los sistemas de generación sean fácilmente ampliables, según se modifiquen las necesidades energéticas de los usuarios, y se acopladas relativamente fácil a sistemas eléctricos ya existentes. Este modularidad es una de las principales características de la GD en contraposición a la generación centralizada (GC) donde ampliar una gran central de generación puede ser muy costoso y complicado, puesto que implica una modificación completa de la infraestructura y equipamiento. La GD es entonces una alternativa muy interesante, puesto que es altamente versátil, para solventar los requerimientos energéticos de los usuarios [6] ayudando además a mitigar las emisiones de gases de efecto invernadero GEI a la atmósfera [7].

Sin embargo, la GD también tiene ciertas desventajas frente a la GC. La principal desventaja de la GD es que al funcionar principalmente con fuentes renovables la producción de energía se ve altamente afectada por la disponibilidad de las fuentes, como lo es la variación de irradiación solar a lo largo de un día por factores climatológicos o la intermitencia del viento. La variabilidad de la disponibilidad del recurso renovable se encuentra muy relacionada en los sistemas actuales con los sistemas solares y eólicos que son las tecnologías de renovables con mayor penetración en la actualidad, cuya potencia que entregan varía según la hora del día y la estación del año, esto desincentiva la adopción de estas tecnologías [8], [9]. Además de los elevados costes económicos actuales de las tecnologías de aprovechamiento, lo cual se traduce en tiempos más largos de retorno de inversión [10], [11].

Para subsanar la intermitencia en la disponibilidad de los recursos renovables para la generación de electricidad en las microrredes y mejorar su eficiencia se han desarrollado diversas técnicas, entre las cuales se encuentran los sistemas de gestión de la energía (SGE), los cuales a través de estrategias de control intentan sacar el mayor partido de las fuentes de energía disponibles, así como de almacenar energía, o inyectar a la red, en función de las condiciones medioambientales, las necesidades energéticas e incluso los precios de la energía en el mercado [12]. De esta manera, una de las principales funciones de los SGE es lograr una operación ordenada y coordinada de las diferentes tecnologías de generación y almacenamiento dentro de una microrred basada en energías renovables [13].

En aras de optimizar el rendimiento de los SGE en microrredes basadas en energías renovables, se ha investigado la implementación de algoritmos de inteligencia artificial (IA) y aprendizaje automático (ML) para la predicción y el ajuste en tiempo real de las estrategias de control. Estos algoritmos permiten una adaptación más rápida y precisa a las variaciones en las condiciones medioambientales, la demanda de energía y los precios en el mercado, lo que resulta en una mayor eficiencia energética y económica. Además, la integración de tecnologías de comunicación avanzadas en los SGE facilita la cooperación entre las distintas unidades de generación y almacenamiento, así como la interacción con la red principal, contribuyendo a la resiliencia y la estabilidad de la microrred en su conjunto. En la Figura 3 se muestran una comparación entre los esquemas centralizados y distribuidos de generación.

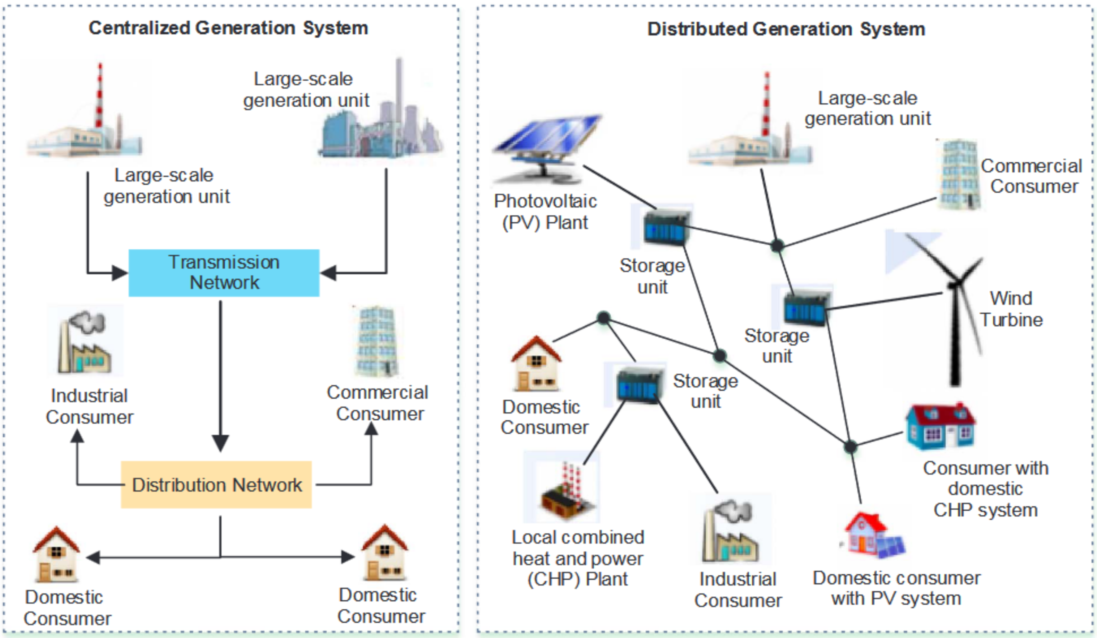

Figura 3 Arquitectura típica del modelo de generación centralizada contra el modelo de generación distribuida. Fuente: [14]

Retomando el concepto de microrred eléctrica, esta puede definirse como el conjunto de unidades de generación y almacenamiento de energía trabajando de manera coordinada para proveer de energía a los usuarios [15], [16]. Las microrredes son la respuesta idónea para los problemas de vulnerabilidad energética, democratización de la energía, reducción de emisión de GEI y aumento de la robustez de los sistemas eléctricos nacionales. El Centro Nacional de Energías Renovables (CENER) de España define a las microrredes como *"[…] una agregación de cargas y micro generadores operando como un sistema único que provee tanto de energía eléctrica como energía térmica"* [17]. Una microrred integra en un todo a diferentes fuentes de energía distribuida, de origen renovable en su mayoría, y sistemas de almacenamiento de energía. La Figura 4 muestra el esquema típico de una microrred.

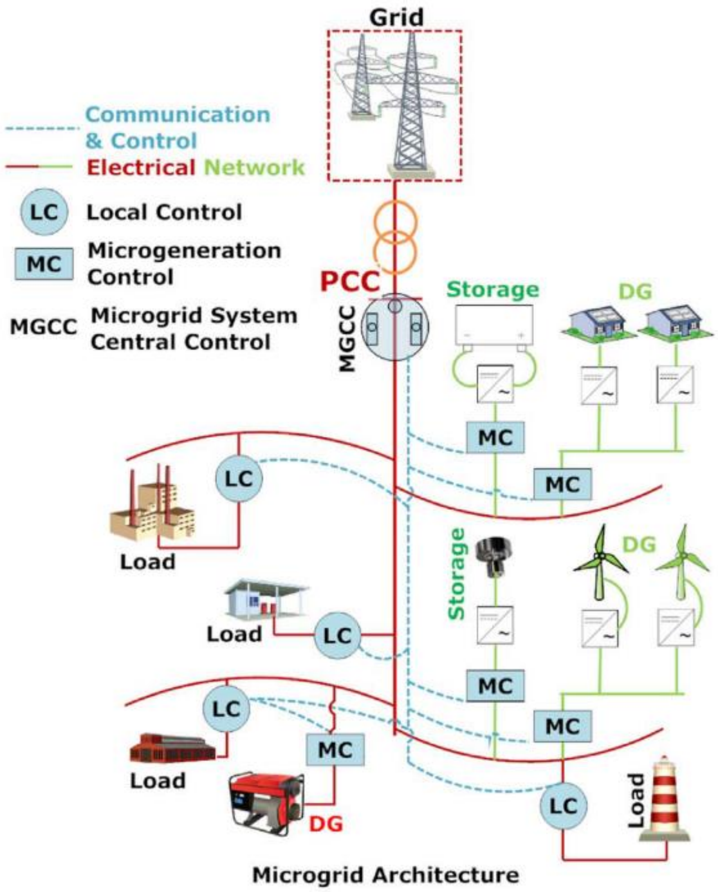

Figura 4 Arquitectura típica de una microrred. Fuente: [18]

En el momento en que una microrred integra tecnologías avanzadas de control y monitoreo esta se convierte en una microrred inteligente. La operación coordinada de las fuentes dentro de la microrred es controlada por el SGE de tal manera que se tenga una respuesta a la demanda [19].

De esta manera entonces, la gestión eficiente de los recursos dentro de una microrred es llevada a cabo por el SGE [20]. Los SGE se pueden clasificar en dos categorías principales, en SGE centralizados y no centralizados [21]. Los SGE centralizados se basan en un controladore central dentro de la microrred, que de acuerdo con la información que este recibe, y conforme a un algoritmo programado, este puede tomar decisiones sobre el flujo de la energía dentro y fuera de la microrred [22]; mientras que los SGE descentralizados no poseen una unidad central de control y monitoreo, sino diferentes nodos con reglas de operación más o menos sencillas capaces de trabajar en conjunto. En las topologías descentralizadas el droop control tiene un importante papel para la gestión de la energía [23]. Los algoritmos convencionales de los SGE se basan principalmente en el balance de energía instantáneo, estos métodos son poco eficaces puesto que no consideran muchas de las complejidades de los sistemas de las microrredes eléctricas [24], como la estimación de la disponibilidad de las fuentes renovables, el aprendizaje histórico en función de datos previos y los hábitos de consumo del usuario, condiciones climáticas y estacionales, así como la compleja dinámica de los sistemas de almacenamiento y el mercado de la energía. Crear un modelo matemático para un SGE de la energía que involucre las no-linealidades antes mencionadas es una tarea muy compleja. Una alternativa para modelar sistemas de esta complejidad es hacerlo mediante el uso de algoritmos de optimización, estos se dividen en clásicos, como lo son técnicas de programación lineal y no lineal, estocástica y optimización de redes; y en metaheurísticos bio-inspirados, los cuales imitan fenómenos de equilibrio de la naturaleza, trasladándolos a métodos computacionales [25]. Los algoritmos metaheurísticos son una herramienta muy poderosa para diversas áreas de la ingeniería. Específicamente en el campo de las microrredes eléctricas la aplicación de algoritmos metaheurísticos ha seguido los siguientes caminos de aplicación: diseño óptimo de sistemas [26], dimensionamiento óptimo [27], control óptimo [28], estimación de recurso y gestión de la energía [29]–[31]. Los algoritmos de optimización aplicados a las microrredes se pueden clasificar en diferentes tipos como se muestra en la Figura 5.

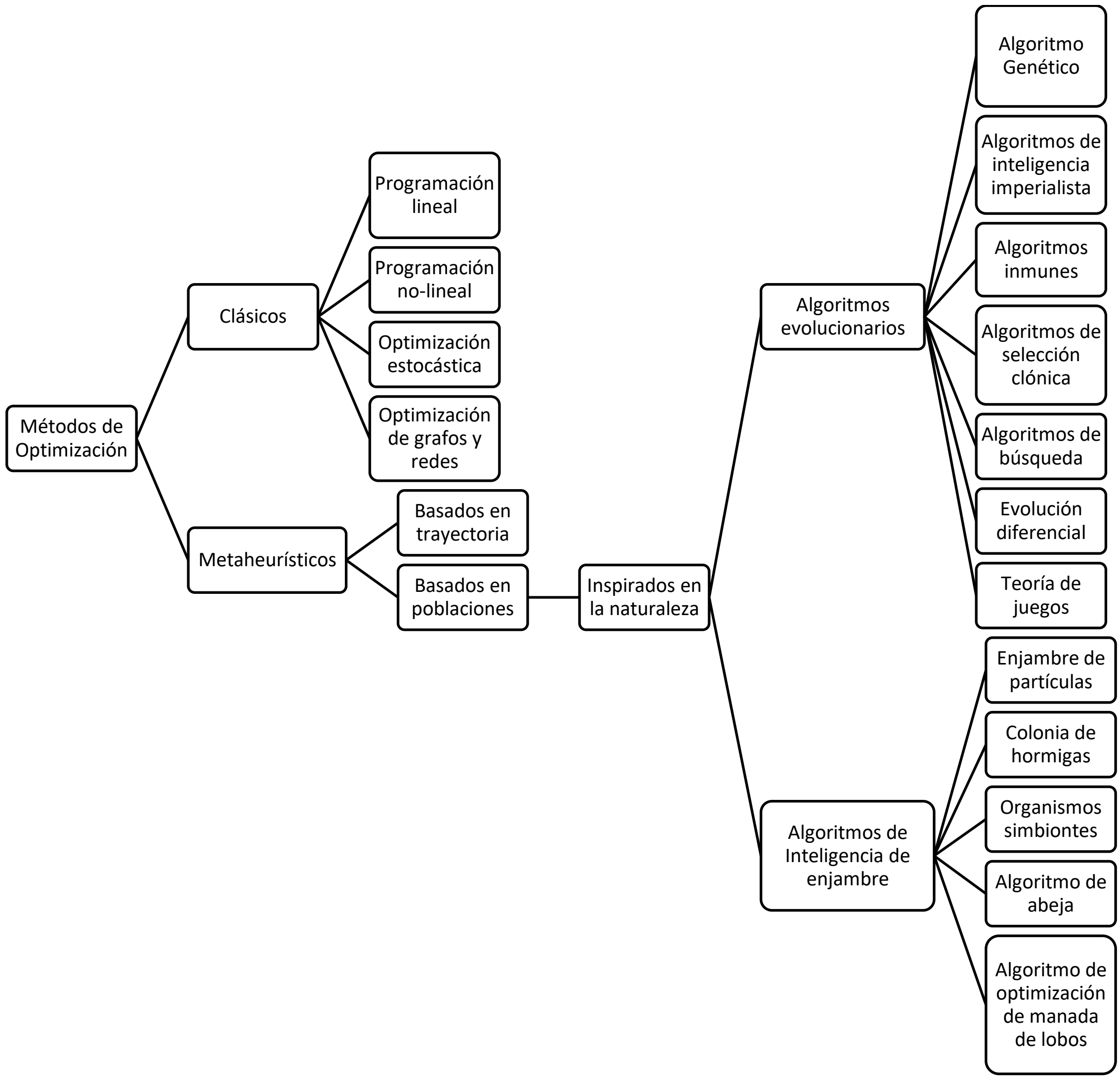

Figura 5 Clasificación de los métodos de optimización aplicados a las energías renovables. Fuente: Elaboración propia.

Las técnicas de optimización son una disciplina matemática mediante la cual es posible encontrar soluciones combinatorias a problemas complejos para encontrar puntos máximos o mínimos [32]. En los sistemas eléctricos es común el diseño de controladores cuya función sea reducir al mínimo el error entre un valor de referencia dado y un valor de salida, por ejemplo, en los convertidores de potencia de las microrredes como en el trabajo de [33] donde se aplican algoritmos de optimización metaheurísticos para mejorar el desempeño de sistemas de convertidores de potencia. Como se mencionó con anterioridad, los algoritmos metaheurísticos imitan el comportamiento de la naturaleza para encontrar de manera inteligente soluciones óptimas de diseño, empleando menos tiempo de cómputo que las técnicas clásicas de optimización. La mayoría de los algoritmos metaheurísticos actuales se basan en mecanismos de selección natural y adaptación social de diversos organismos. En la Figura 6 se muestran la distribución por país de publicaciones científicas relacionadas con algoritmos de optimización aplicados a las energías.

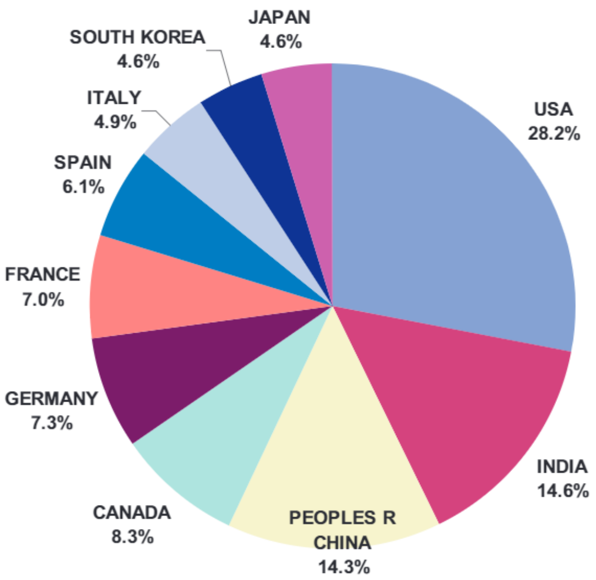

Figura 6 Distribución por país de publicaciones científicas sobre algoritmos de optimización aplicados a energías renovables para el 2011. Fuente: [34].

Además del uso de algoritmos de optimización para la mejora del desempeño y eficacia de sistemas de ingeniería, el uso de redes neuronales artificiales (RNA) ha cobrado atención en años recientes para aplicaciones de modelado predictivo y control, gracias a su gran robustes y facilidad de uso para modelar sistemas altamente complejos como lo son las microrredes eléctricas [35], [36]. Las RNA se basan en emular el funcionamiento de las redes neuronales naturales, sobre todo los procesos de aprendizaje reforzado con base a experiencias pasadas del cerebro biológico. De manera análoga a como lo hace una red neuronal biológica una RNA es capaz de aprender a través de datos históricos, esta capacidad puede ser aprovechada para poder hacer que los sistemas de ingeniería sean capaces de responder ante situaciones para las cuales no fueron originalmente programados, y adaptarse a cambios [37].

Puesto que las microrredes son sistemas complejos y no lineales, los algoritmos metaheurísticos de optimización son una buena opción para encontrar configuraciones óptimas de estos sistemas. En este trabajo de investigación se ha hecho una revisión sobre el estado del arte y la técnica relacionados al control de microrredes para la creación de un modelo de un sistema de gestión óptima para una microrred empleando algoritmos bio-inspirados. En las siguientes secciones del presente documento se detalla la motivación, objetivos y metodología seguidos.

1.2 Motivación

La generación centralizada de energía está cambiando a un sistema más dinámico y descentralizado, donde los usuarios de energía no son solamente consumidores, sino que además producen, a dichos usuarios se les llama prosumidores. Este cambio se está logrando gracias a la cada vez mayor penetración de las fuentes renovables en los esquemas de generación, haciendo que la integración de tecnologías de la información sea parte importante para el monitoreo y control de estos sistemas cada vez más complejos [38]. A nivel mundial, diversos países han firmado compromisos para la reducción de emisiones de GEI, siendo esto una de las principales políticas que impulsa la integración de tecnologías de fuentes renovables de energía y la migración a esquemas de GD. Se estima que la demanda de energía a nivel mundial habrá crecido un 44% entre 2006 y 2030, con lo cual se habrá aumentado en un 77% la capacidad de generación [39], considerando los datos de la IEA, más de un 12% será de origen renovable, por lo que una parte importante de inversión económica será en tecnologías y sistemas de control y monitoreo para redes inteligentes de energía.

Desafortunadamente, la energía proveniente de fuentes renovables está en declive en algunos países de América Latina, como por ejemplo México, esto debido a políticas internas que favorecen la generación empleando fuentes tradicionales de energía [40] esto es un importante reto en materia de sostenibilidad para la región; mientras que, a nivel global, la energía proveniente de fuentes de energías renovables (ER) crece de manera sostenida. La Figura 7 muestra las tendencias de crecimiento del consumo de energía global y la Figura 8 muestra la inversión global en infraestructura de energía por fuente de origen.

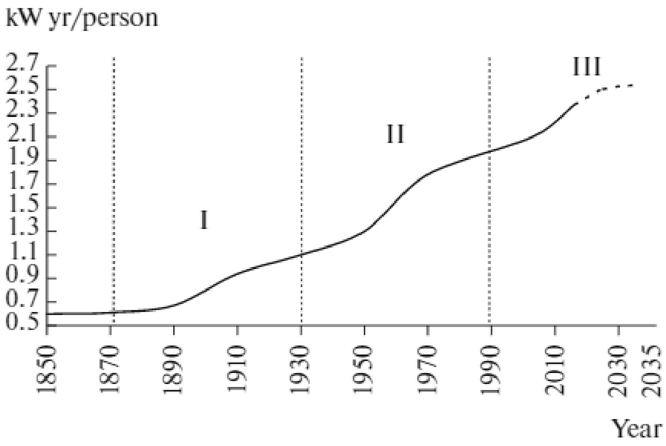

Figura 7 Tendencias de crecimiento del consumo energética a nivel global. Fuente: [41]

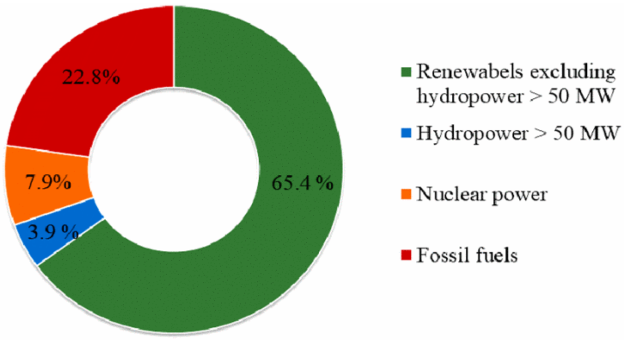

Figura 8 Inversión en fuentes de energía a nivel global. Fuente: [42]

El cambio de un esquema de GC a un esquema de GD e inteligente es un elemento clave en la lucha contra el cambio climático, además de la democratización de la energía y la reducción de la vulnerabilidad y pobreza energética en comunidades rurales y marginadas. La integración de tecnologías de ER en los sistemas de GD es clave. Sin embargo, estos sistemas al depender de fuentes de ER altamente dependientes del medio ambiente, se requiere entonces de un SGE que optimice los recursos disponibles para poder cubrir la demanda de energía.

El desarrollo de SGE para microrredes es un tema de interés para la comunidad científica [43]. Se busca que la microrred sea un sistema controlable y flexible que puede operar tanto en modo aislado como interconectado a la red eléctrica para la realización de transacciones de compra/venta de energía según las necesidades y condiciones [32].

Uno de los principales retos que las microrredes enfrentarán es la gestión múltiple de la energía y la información, es decir, el intercambio de la energía hacia fuera y dentro de la microrred [44]. El mismo intercambio de información en la microrred es un reto en sí, puesto que existe preocupación en temas de seguridad y privacidad de los datos manejados [45]. Las microrredes presentan mayores desafíos de estabilidad cuando están operando de modo aislado, puesto que no cuentan con el apoyo de la red eléctrica. Una manera de aumentar la estabilidad de microrredes en modo aislado es mediante estrategias de conexión/desconexión de cargas no prioritarias, como lo mostrado en el trabajo de [46] que propuso un modelo utilizando una simulación mediante diversos algoritmos bio-inspirados, con la desventaja que su respuesta fue lenta debido a la complejidad del problema y su formulación. Por otra parte, en [47] se propone un sistema de lógica difusa capaz de hacer un monitoreo de la calidad de la energía a través de un conjunto de 256 reglas, sin embargo, este modelo al igual que el anterior consume una cantidad importante de tiempo por la cantidad de cálculos que el algoritmo debe realizar. Otro enfoque que se ha probado para la gestión de microrredes es mediante la priorización de la reducción del coste de la energía en función de la demanda y la disponibilidad de recursos como en el trabajo de [48], donde el modelo posee una gran cantidad de calculaciones, pero satisface de manera limitada los requerimientos energéticos del usuario, al dar prioridad a la reducción de costos monetarios. En el trabajo de [49] se explora el enfoque de la estabilidad considerando un entorno multi-microrred a través de una estrategia de *self-healing* a través de la cual se selecciona la fuente o microrred más adecuada en términos de los costes energéticos.

Con base en lo antes expuesto, este trabajo de investigación tiene como principal motivación la creación de un modelo de gestión de la energía para una microrred empleando algoritmos bio-inspirados, partiendo de un enfoque integrador y sistémico desde el control primario hasta el terciario para una microrred, e hibridando tanto algoritmos de optimización como redes neuronales artificiales, para dar una mayor versatilidad al sistema y mejorando lo que se encuentra publicado en bibliografía científica. En la siguiente sección se detallan los objetivos del presente trabajo de tesis.

1.3 Objetivos

El objetivo principal del presente trabajo de investigación es desarrollar un modelo de gestión óptima de la energía para una microrred, incorporando algoritmos bio-inspirados, este modelo se ha validado mediante ensayos experimentales, y puede ser extrapolado y aplicado a cualquier microrred.

Para lograrlo, se han planteado los siguientes objetivos específicos:

- Experimentar y validar la funcionalidad de algoritmos de bio-inspirados de optimización sobre convertidores de potencia.

- Integrar algoritmos bio-inspirados y redes neuronales artificiales para determinar el modo de operación de una microrred.
- Implementar un modelo de gestión de la energía para una microrred basado en algoritmos bio-inspirados.

1.4 Metodología

La investigación doctoral se llevó a cabo en tres etapas bien definidas, con el objeto de mejorar el control de una microrred mediante la integración de diversos algoritmos y técnicas metaheurísticas (ver Figura 9). Cada etapa se describe a continuación:

1. Revisión del estado del arte: En esta etapa se realizó una revisión exhaustiva del estado actual de la técnica en cuanto a la aplicación de algoritmos bio-inspirados en sistemas energéticos. Se recopilaron y analizaron diversos estudios previos para poder identificar tendencias y desarrollos en este campo de la investigación.
2. Mejora del control primario de la microrred: En esta etapa la investigación se centró en mejorar el control primario de la microrred a través de la optimización de los convertidores de potencia asociados a la misma. Se seleccionaron diferentes algoritmos de optimización bio-inspirados, los cuales fueron evaluados y comparados entre sí, así como también comparados con algoritmos y controladores tradicionales para convertidores de potencia. Se realizaron simulaciones para evaluar su desempeño y determinar cuál sería el algoritmo más adecuado para la optimización del control primario de la microrred aplicado a convertidores de potencia.
3. Mejora del control secundario y terciario de la microrred: La investigación continuó en esta etapa con la evaluación y selección de algoritmos bio-inspirados con el objetivo de mejorar ahora el control secundario y terciario de la microrred. Se realizaron hibridaciones entre algoritmos bio-inspirados y redes neuronales artificiales para mejorar tanto el desempeño de la microrred como su capacidad de previsión en función de condiciones medio ambientales y pronósticos de demanda de energía. Los resultados obtenidos fueron evaluados mediante comparaciones con datos experimentales de pruebas reales, utilizando criterios e índices de desempeño muy específicos descritos en detalle en cada una de las publicaciones científicas generadas en esta etapa.

Para consultar información más detallada sobre la metodología utilizada en cada una de las etapas descritas con anterioridad se recomienda consultar las publicaciones presentadas en el Capítulo 2 de este documento.

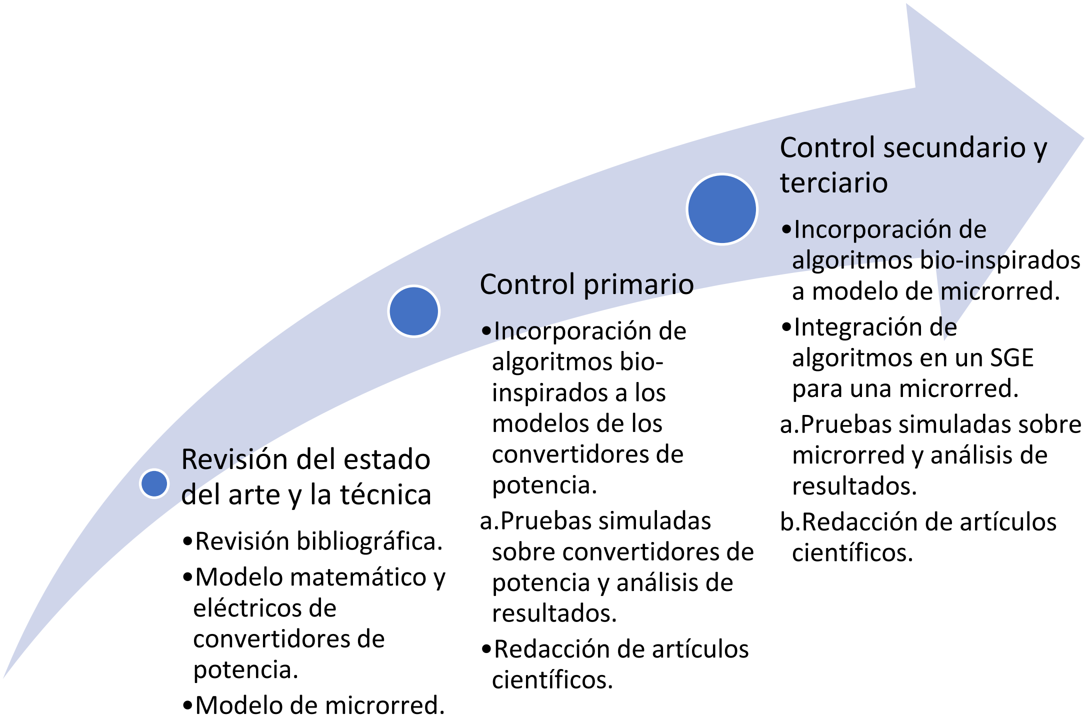

Figura 9 Metodología general de la investigación. Fuente: Elaboración propia.

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Capítulo 2.
Publicaciones científicas

En esta tesis se presenta y analiza el uso de algoritmos bio-inspirados en el ámbito de la optimización y el control de sistemas eléctricos, con especial énfasis en microrredes eléctricas híbridas. En este capítulo se presentan cinco publicaciones científicas que abordan el tema de la optimización de controladores y modelos de gestión energética utilizando algoritmos bio-inspirados y tradicionales. En cuanto al orden cronológico de las publicaciones, es de destacar que no se corresponde del todo al orden presentado en esta tesis, esto debido en parte a que se comenzó trabajando la microrred de la más integral posible.

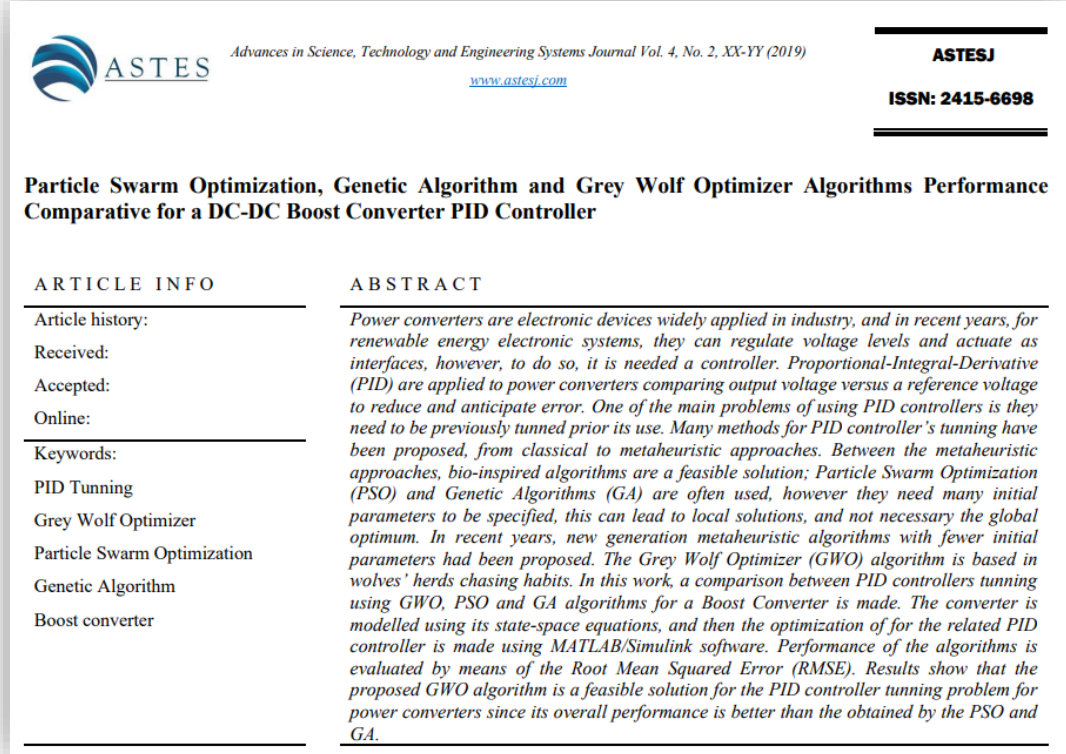
La primera publicación, titulada "Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller", se centra en comparar el rendimiento de tres algoritmos bio-inspirados (enjambre de partículas, algoritmo genético y optimizador lobo gris) para el controlador PID de un convertidor DC-DC. Los resultados muestran una buena adaptabilidad de los algoritmos bio-inspirados a este tipo de sistema y una mayor eficiencia en comparación con técnicas clásicas.

La segunda publicación, titulada "Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms", se enfoca en la optimización del controlador de punto máximo de potencia de un sistema fotovoltaico mediante el uso del optimizador lobo gris. Se realiza una comparativa con técnicas tradicionales y se demuestra la mejora en términos de rapidez de convergencia y rendimiento final.

La tercera publicación, titulada "Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach", se centra en el desarrollo de un modelo de gestión energética para una microrred eléctrica híbrida autónoma mediante el uso de enjambre de partículas y redes neuronales. Se muestra la capacidad del modelo para adaptarse a diferentes condiciones y optimizar el uso de los recursos energéticos.

Por último, la cuarta publicación, "A multimicrogrid energy management model implementing an evolutionary game-theoretic approach", presenta un modelo de gestión energética para una multimicrored utilizando un enfoque teórico de juegos evolutivos.

2.1 Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller



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ABSTRACT

Power converters are electronic devices widely applied in industry, and in recent years, for renewable energy electronic systems, they can regulate voltage levels and actuate as interfaces, however, to do so, it is needed a controller. Proportional-Integral-Derivative (PID) are applied to power converters comparing output voltage versus a reference voltage to reduce and anticipate error. One of the main problems of using PID controllers is they need to be previously tunned prior its use. Many methods for PID controller's tunning have been proposed, from classical to metaheuristic approaches. Between the metaheuristic approaches, bio-inspired algorithms are a feasible solution; Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are often used, however they need many initial parameters to be specified, this can lead to local solutions, and not necessary the global optimum. In recent years, new generation metaheuristic algorithms with fewer initial parameters had been proposed. The Grey Wolf Optimizer (GWO) algorithm is based in wolves' herds chasing habits. In this work, a comparison between PID controllers tunning using GWO, PSO and GA algorithms for a Boost Converter is made. The converter is modelled using its state-space equations, and then the optimization of for the related PID controller is made using MATLAB/Simulink software. Performance of the algorithms is evaluated by means of the Root Mean Squared Error (RMSE). Results show that the proposed GWO algorithm is a feasible solution for the PID controller tunning problem for power converters since its overall performance is better than the obtained by the PSO and GA.

Aguila-Leon, J., Chiñas-Palacios, C., Carlos, V. S., Hurtado-Perez, E., & Garcia, E. X. M. (2021). Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller. Advances in Science, Technology and Engineering Systems Journal, 6(1), 619-625.

En este artículo se explora el control primario aplicado a los controladores de convertidores de potencia, específicamente un convertidor elevador. Se presenta la metodología desarrollada para integrar algoritmos bio-inspirados a un controlador PID para aumentar la estabilidad y mejorar los tiempos de respuesta del sistema ante diferentes perturbaciones. Se hace una comparativa con otros algoritmos y técnicas clásicas de control.

Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller

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Abstract

Power converters are electronic devices widely applied in industry, and in recent years, for renewable energy electronic systems, they can regulate voltage levels and actuate as interfaces, however, to do so, is needed a controller. Proportional-Integral-Derivative (PID) are applied to power converters comparing output voltage versus a reference voltage to reduce and anticipate error. Using PID controllers may be complicated since must be previously tuned prior to their use. Many methods for PID controllers tuning have been proposed, from classical to metaheuristic approaches. Between the metaheuristic approaches, bio-inspired algorithms are a feasible solution; Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are often used; however, they need many initial parameters to be specified, this can lead to local solutions, and not necessarily the global optimum. In recent years, new generation metaheuristic algorithms with fewer initial parameters had been proposed. The Grey Wolf Optimizer (GWO) algorithm is based on wolves' herds chasing habits. In this work, a comparison between PID controllers tuning using GWO, PSO, and GA algorithms for a Boost Converter is made. The converter is modeled by state-space equations, and then the optimization of the related PID controller is made using MATLAB/Simulink software. The algorithm's performance is evaluated using the Root Mean Squared Error (RMSE). Results show that the proposed GWO algorithm is a feasible solution for the PID controller tuning problem for power converters since its overall performance is better than the obtained by the PSO and GA.

Introduction

Power converters have an important role in Industry applications; their main purpose is to regulate power in electronic appliances and adjusting current and voltage signals to desired levels by a high frequency switching control device [1,2]. One of the most significant modern applications for power converters is related to Renewable Energy Sources (RES), since the power generated for these sources highly depends on environmental conditions power converters are a reliable solution to stabilize output voltage and current of RES. A Boost Converter is an electronic device whose main purpose is to raise an input voltage and stabilize it to a desired highest level [3,4]. Since voltage regulation on power converters, and therefore, boost converters, depends on a switching signal, is needed a controller to generate a proper pulse width modulation (PWM) to modify the duty cycle of the switching signal. PID controllers are commonly used for this kind of applications, however, PID controllers need to be tuned prior its use [5]; The PID controller tuning can be a challenging task, many methods had been proposed for this purpose, from classical modeling and analysis based on system response [6] to modern techniques based on metaheuristic algorithms [7]. Nature had been an inspiration for modern metaheuristic algorithms, most of them based on animal behavior, for system design and control optimal parameters finding [8]. Bio-inspired algorithms imitate animal collective intelligence to explore, find, and exploit food and resources. Collective intelligence is the sum of individual behavior based on simple rules, and these behaviors and strategies can be translated into computational optimization algorithms. The most common bio-inspired algorithms are Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) algorithms. Among these bio-inspired optimization algorithms applications are control of load frequency [9], systems optimal sizing and design [10], power flow applications [11], predictive control for microgrids based on renewable energies [12], power converters optimal design [13] and regulation for voltage [14]. In [15] a novel application of the Genetic Algorithm (GA) for manufacturing process using Electrical Discharge Machining (EDM) is presented, the authors found that using GA can improve the EDM output for manufacturing. Also, GA had been applied to face recognition [16] and e-commerce user personalized recommendation in multi-criteria recommender systems [17]. The PSO algorithm imitates in a general basis animal behavior, each animal is represented by a particle that explores its environment searching for food. In [18], an evolutionary approach using Symbiotic Organisms Search (SOS) algorithm, which is based on PSO algorithms and the trophic chain of the ecosystems, and a two-round fuzzy inference engine were presented for energy management in microgrids. Authors in [19] propose a controller based on Fuzzy-PID in combination with a PSO algorithm to adjust the controller parameters for a resistance furnace, they found a better system response compared to classical PID controller tuning technics for that application. Since PSO is general modeling for animal behavior, there had been developed and studied variants of PSO based on particular animal species [20,21]. Authors in [22] applied a Whale Optimization Algorithm for an optimal design of a PID controller for a DC-DC converter using a transfer function and step response approach to analise the system performance; they found beter transciente response in comparison to a compared GA algorithm, however, they did not considered fluctutanting input voltages or load changes. In 2014 S. Mirjalili and A. Lewis (2014) presented the Grey Wolf Optimizer (GWO), based on hunting strategies of wolves herds [23]. The GWO had been studied in comparison to other optimization algorithms as well as some engineering applications. Authors in [24] applied GWO to a PID controller to optimize the system response of a steam pressure system, they found an improvement in system stability and response. In [25] the GWO was applied to a modeled levitation system, improving time domain response and reducing the system error in comparison to the PID tuning MATLAB tool. Also, GWO had been applied to power systems, in [26] authors presented a an application of GWO optimizer for FACTS allocation.

In this paper, an optimal tuning for a PID controller using the GWO algorithm applied to a boost converter is presented. The boost converter is modeled unsung state-space equations and then simulated in MATLAB/Simulink. The proposed GWO-PID tuned algorithm performance is compared with PSO and GA algorithms in terms of the RMSE and the system response for variable load and variable input voltage.

The paper is organized as follows: Section 2 depicts the boost converter model and description. Section 3 presents the GWO, PSO, and GA optimization algorithm basis. Section 4 shows the optimization methodology for the boost converter. Section 5 summarizes the results and, finally, Section 6 are the conclusions of this study.

Mathematical model of the Boost Converter

The boost converter is an electronic device that rises input voltage to the desired highest output voltage. Voltage regulation is made by a PWM signal, applied to an inductor (L) and capacitor (C) arrangement, carried out by a fast-switching transistor that according to the control signal. Changes in the PWM signal modifies the L-C charge and discharge cycles and change the output signal [27]. The boost converter configuration is shown in Figure 1.

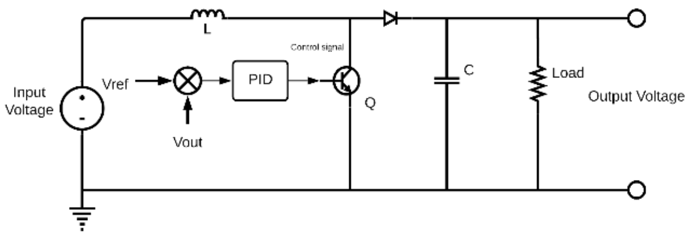

Figure 1: Electric diagram for the Boost converter.

Modeling of the boost converter was carried out using state-space equations, then MATLAB/Simulink software was used for simulation.

State-space equations were obtained employing Kirchhoff's voltage and current laws analysis for each system switching state determined by the u control signal value. Since u the signal can only adopt a 1 o 0 value, there are two possible Boost converter electric configurations, that correspond to charge and discharge cycles for the L and C elements. The two possible circuit configurations are condensed in a single matrix form of state-space equations as showed in (1).

$$\begin{bmatrix} \frac{dv_o(t)}{dt} \\ \frac{di_L(t)}{dt} \end{bmatrix} = \begin{bmatrix} \frac{1-u}{C} & -\frac{1}{CR} \\ 0 & -\frac{1-u}{L} \end{bmatrix} \begin{bmatrix} v_o(t) \\ i_L(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{L} \end{bmatrix} v_i(t) \tag{1}$$

In (1) L is the inductor, C is the capacitor, $i_L(t)$ is the current in the inductor, $v_o(t)$ is the output voltage, $v_i(t)$ is the voltage ant input of the boost converter, and u is the PWM control signal generated by the PID controller.

Optimization Algorithms

A performance comparison between three optimization algorithms: PSO, GA, and GWO is presented in this paper, the main objective of this research is to get insights on the best optimization algorithm for PID controllers tuning applied to a power converter. A brief description of each of the optimization algorithms is presented in the following subsections.

Grey Wolf Optimizer

Wolves had a strong hierarchy inside their herds, they are organized in a group of 5 to 12 wolves. Each herd had a leading wolf, called alpha α wolf; secondary wolves called beta β wolves; wolves subordinated to α and β wolves are delta wolves δ ; and finally, follower wolves are omega ω wolves. The optimization using the GWO is carried out in three main stages that mimic the hunting process of grey wolves' herds in nature: encircling, hunting, and attacking.

Encircling stage:

In this stage, each wolf updates its position in the search space according to the relative best position to prey, dictated for α wolf. The encircling and corral behavior of the prey is modeled mathematically by (2-5).

$$\vec{X}(t+1)=\vec{X}_{pos}(t)-\vec{A}\vec{D} \quad (2)$$

$$\vec{A}=2ar_1-a \quad (3)$$

$$\vec{C}=2r_2 \quad (4)$$

$$\vec{D}=\left|\vec{C}\vec{X}_{pos}(t)-\vec{X}(t)\right| \quad (5)$$

Where $\vec{A}$ and $\vec{C}$ are vectors of coefficients, $\vec{X}_{pos}$ vector is the position of the prey, $\vec{X}$ vector is the position of the wolf, t is current iteration, r_1 and r_2 values randomly generated between zero and one, and, vector a value decreases linearly according to iterations. The vector D represents the distance between the current position of the wolf and the position of a pack leader (alpha, beta, or delta). The encircling stage is the phase in which grey wolves attempt to surround and approach their prey.

Hunting stage:

The position of wolves is rearranged according to their proximity to the prey. The wolf with the closest distance to the prey is assigned to be the alpha α wolf, β and δ wolves are assigned according to their position to prey. Equations (6-8) describe the wolve position updating.

$$\vec{X}_i(t+1)=\frac{\vec{X}_{i1}+\vec{X}_{i2}+\vec{X}_{i3}}{3} \quad (6)$$

$$\left.\begin{aligned}\vec{X}_{i1}&=\vec{X}_\alpha(t)-\vec{A}_1\vec{D}_\alpha\\ \vec{X}_{i2}&=\vec{X}_\beta(t)-\vec{A}_2\vec{D}_\beta\\ \vec{X}_{i3}&=\vec{X}_\delta(t)-\vec{A}_3\vec{D}_\delta\end{aligned}\right\} \quad (7)$$

$$\left.\begin{aligned}\vec{D}_\alpha&=\left|C_1\vec{X}_\alpha(t)-\vec{X}_i(t)\right|\\ \vec{D}_\beta&=\left|C_2\vec{X}_\beta(t)-\vec{X}_i(t)\right|\\ \vec{D}_\delta&=\left|C_3\vec{X}_\delta(t)-\vec{X}_i(t)\right|\end{aligned}\right\} \quad (8)$$

Where $\vec{X}_{i(t+1)}$ is the wolf that has the best position to the prey and i is the current iteration number of the GWO algorithm.

Attack stage:

Attack to prey occurs when the heard is upon the prey, before this, it is necessary to minimize the distance between wolves and the prey. The prey is the optimization problem's best global solution.

Must be defined as a vector A, shown in(3), to make a decreasing coefficient dependent on the T iteration number. The vector A value is reduced as the value index a value is reduced according to (9).

$$a = 2 - t\left(\frac{2}{T}\right) \tag{9}$$

The GWO pseudo code is as follows,

GWO: pseudo code.

Result: The best set of particles for the fitness function.
X generation; creation of an initial population of wolves.
Parameters initialization (a,A,C);
Evaluation of position X(0);
Selection of new (a , β and δ);
Selection of new position X(0);
for *e = 1 to MaxIteration* **do**
  for *each wolf*$_i$ *in* ω set **do**;
    for *i = 0 to* DIMENSION **do**;
      Position(*i,j*) updating;
    end for
    Change (a,A,c) factors;
    Calculate *X(t+1)* position
  end for
end for

Particle Swarm Optimization

PSO algorithms are based upon the swarm behavior that some animal species show when they search for resources in their environment. Since PSO is based on collectiveness, each search agent must be modeled. For this purpose, agents are modeled as particles of a swarm, having their position relative to exploration space, velocity, and acceleration rates. At the beginning of the PSO algorithm, several particles are set up in a search space where somewhere in is the global solution for the optimization problem. Finding a global solution depends on the evaluation and minimization of the defined objective function. Iteration by iteration positions, velocities, and acceleration of particles are updated to converge to the global solution. For each particle, a fitness function is numerically evaluated. The best value obtained for all the particle's fitness function is called to be the best global g_{best}. During the iteration process, each best particle fitness function value is called to be the personal best p_{best} . During iterations, the speeds of the particles are accelerated toward the best global solution and the best personal according to (10).

$$v_n = w * v_n + c_1 rand() * (g_{best,n} - x_n)$$

$$+ c_2 rand() * (p_{best,n} - x_n) \tag{10}$$

Where v_n is the speed update of particles, w is a factor of inertia whose value is decreased from 0.9 to 0.4 over time, c_1 and c_2 are coefficients of acceleration pointing to the best global and the best personal.

Genetic Algorithm

Genetic Algorithms are based on the genetic evolution process, imitating the genes mutation and crossover to create the best-adapted organisms to the environment. Mathematical modeling of these mechanisms allows the algorithm to refine solutions carrying out artificial genes crossover, while the mutation mechanism adds uncertainty to experiment with not expected genes, this makes the algorithm avoid local solutions where it could be trapped. During iterations, the best set of artificial genes is obtained, and therefore, a best-adapted species to the environment. The best group of genes for i generations are said to be the found best solution for the optimization problem.

GA can be expressed as a four-step algorithm,

Step 1. An initial population is created. Crossover rate and mutation rate are randomly generated; generation number is setup.

Step 2. Is evaluated the defined fitness function for each set of artificial genes.

Step 3. Starts the crossover process and mutation process to set the next generation of artificial genes.

Step 4. Return to Step 2 until the stop criterion is reached.

Tuning of a PID controller for a Boost converter using optimization algorithms

PID controllers allow the system to operate near desired output values, ensuring good response in the face to possible disturbances. The proposed Boost Converter includes a PID controller for voltage regulation for load changes. The PID controller carries out proportional, integrative, and derivative actions to reduce and prevent error $e(t)$ between output and reference signals of the system. The controller signal $u(t)$ is mathematically modeled according to (11).

$$u(t) = K_p e(t) + \frac{K_p}{T_i}\int_0^t e(t)dt + K_p \frac{T_d de(t)}{dt}] \tag{11}$$

In (11) K_p, T_i and T_d are the proportional, integration time and derivation time constants, respectively. By adjusting the values of these constants, the error in the system can be reduced. The integration and derivative time can be expressed in terms of K_p according to (12-15).

$$K_p = k \tag{12}$$

$$K_i = {K_p}/{T_i} \tag{13}$$

$$K_d = K_p T_d \tag{14}$$

Where k is the constant of proportional gain K_p, K_i is the constant of integrative gain, and K_d is the constant of derivative gain for the PID controller. The goal of the GWO, PSO, and GA algorithms is to find the best K_p, K_i, K_d values so the error $e(t)$ is minimized. A vector X is defined to include the constant values according to (15). To minimize the Error $e(t)$ the Root Mean Squared Error (RMSE) is defined to be the objective function for the optimization problem according to (16).

$$\vec{X} = [K_p, K_i, K_d] \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{t=0}^{T_{sim}} \left(v_{out}(t) - v_{reference}(t)\right)^2}{T_{sim}}} \tag{16}$$

Where T_{sim} is simulation time, $v_{out}(t)$ is the output voltage of the power converter, and $v_{reference}(t)$ is the reference voltage signal. The Figure 2 illustrates the overall flowchart for the optimization to find the values for the PID controller constant gains using the GWO, PSO, and

GA, the first step of all three algorithms evaluated is to generate a random search agent population, that according to the algorithm is the number of wolves, particles, or gene population, then for each agent, the objective function is evaluated in an iterative loop until the best solution is found.

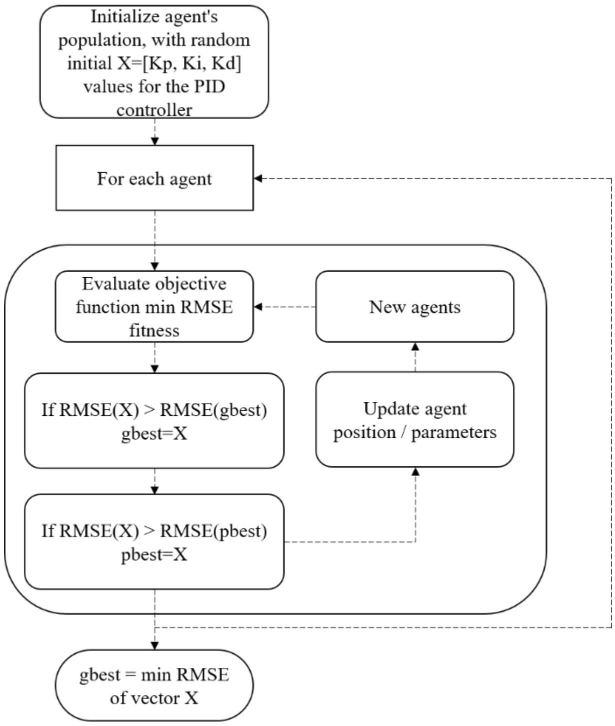

Figure 2: Overall flowchart for the optimization to find the optimal values PID controller constant gains for the proposed optimization algorithms.

Simulation, results, and discussion

The optimization algorithms of GWO, PSO, and GA were implemented using MATLAB and Simulink software. Several simulations run for each of these algorithms were performed to find the best PID controller gains values. The difference between each run is the variation of the limits of the search space for the optimization variables, that is, different minimum and maximum values for each gain constant of the controller. A scan was made with different values to determine the search space with the best possible solution for the algorithms evaluated for this particular application. The Boost Converter configuration parameters are shown in Table 1.

Table 1: Boost Converter Configuration.

Description	Value	Units
Capacitor	250	μF
Inductor	1.5	mH
Input voltage	12	V
Reference voltage	24	V
Load	3-15	Ω

Since optimization algorithms require some constant parameters, these values must be specified at the beginning of each test. One of the most significant benefits of using GWO is that fewer initial parameters are required in comparison to PSO and GA. The parameters initial values for each algorithm used in this work are shown in Table 2. For all three optimization algorithms, the search space limits for K_p, K_i and K_d were varied from 0 to 100 for each PID controller gain.

Table 2: Algorithm parameters initial values.

Algorithm	Initial Values	
	Description	***Value***
GWO	Wolves number	12
	Maximum Iterations	7
PSO	Particles	50
	Factor of inertia	0.4-0.9
	Weight of self-adjustment	3
	Weight of social adjustment	1
GA	Size of populations	50
	Rate of crossover	0.9
	Rate of mutation	0.6
	Maximum generations	120

The Table 3 summarizes the PID controller constant gains obtained after the simulation process for each algorithm. The performance is evaluated using RMSE.

Table 3: Best PID gains values and RMSE.

Parameter	**Algorithm**		
	GWO	***PSO***	***GA***
K_p	0.0532E-5	1.7223E-5	0.1269E-5
K_i	1.6048	2.8391	4.0815
K_d	4.8572E-5	7.2477E-5	4.1911E-5
T_i	3.3151E-7	6.0664E-6	3.1092E-7
T_d	91.3008	4.2082	33.0268
$RMSE$	1.0683	2.1755	2.2367
Simulation time (s)	1286	1997	1175

As observed in Table 3, the obtained PID controller gains for all the three algorithms had no significant value for de K_d constant, in this sense, the proposed controller built by the metaheuristic algorithms is a PI controller. Using (13) and (14) it is possible to calculate T_i and T_d for each PID controller tuned by the three algorithms, as shown in Table 3. For a greater T_i than K_p value a significative integrative action of the controller is observed according to (11) and (13); and when K_p value is much smaller than T_d the PID controller will have a small derivative action over the plant, according to (11) and (14). The controller performance evaluated by the RMSE shows that the GWO has the lowest error since its RMSE is about 50.89% lower than the one obtained by the PSO and 44.70% lower than the one obtained using the GA. Since the three evaluated algorithms differ in their search mechanisms, different convergence curves to the best solution found by GWO, PSO and GA algorithms were found. The Figure 3 shows the convergence curve for each of the evaluated algorithms for the Boost converter PID controller tuning optimization problem.

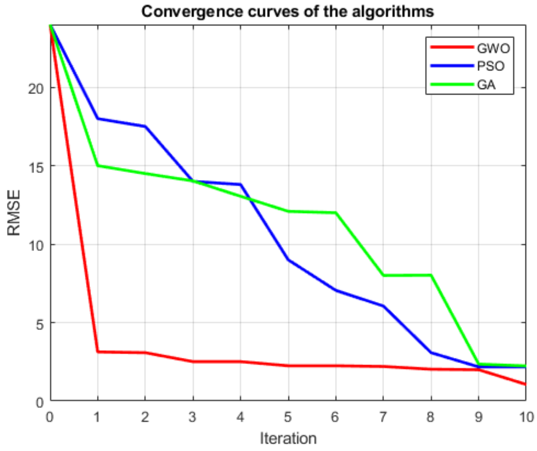

Figure 3: Convergence curves to the best solution found by GWO, PSO, and GA algorithms.

As can be observed in Figure 3, the GWO algorithm is faster to get closer to the best solution set of K_p, K_i and K_d in comparison to PSO and GA whose convergence curves are slower to decrease the resulting RMSE value.

Once the GWO was chosen as the best algorithm for this application, more simulation runs were made varying the search space limits for the optimization variables and with a different number of wolves to ensure a more refined PID gains constants optimal solution for the Boost Converter. The main results of this second round of tests made with the GWO are shown in Table 4.

Table 4: Second round of test for GWO algorithm.

Run	**Obtained optimal values**					
	Search space limits [Kp, Ki, Kd]	***Kp***	***Ki***	***Kd***	***RMSE***	***T***
1	[0-10,0-10,0-10]	0.0012	0.8681	0.0502E-3	1.1436	948.43
2	[0-0.5,0-5,0-0.5]	0.0025	0.7626	0.0263E-5	1.1099	968.40
3	[0-0.25,0-2.5,0-0.25]	0.0191	0.0167	0.0098E-3	8.6105	953.45
4	[0-0.01,0-0.5,0-0.01]	0.0033	0.3118	2.9451E-5	0.7768	9030.77
5	[0-5,0-32,0-0.005]	0.0532E-5	1.6048	4.8572E-5	1.0683	1286.00

As observed in Table 4, the best PID controller gains were obtained in run number four, where the RMSE is minimum with a value of 0.7768. Different RMSE results were obtained for different search space limits; the best results were obtained for the search space limit of [0 to 0.01, 0 to 0.5, 0 to 0.01] corresponding to the $\vec{X} = [K_p, K_i, K_d]$ optimization variables vector. However, when plotting the system, see Figure 4, response for each run, it is found that the system response of the fifth run, with an RMSE of 1.0683, has a faster response to achieve the reference voltage depicts the higher oscillation rates obtained. Best PID controller gains values must be selected according to the needs: a faster response with oscillations, or a slower response with fewer oscillations. The fifth run is chosen as the best solution since a faster response is desirable for this application.

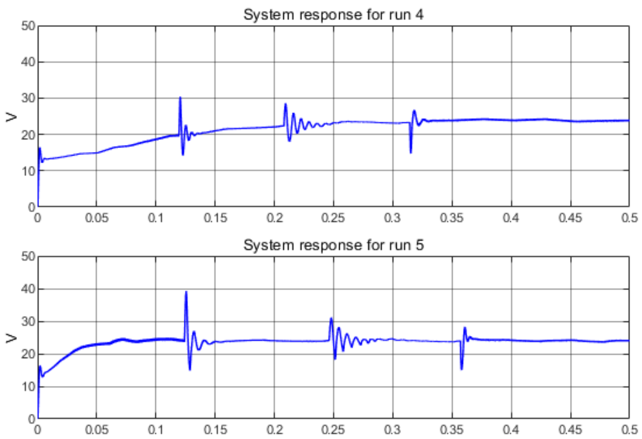

Figure 4: Comparison between run 4 (a) and run 5 (b)for the best GWO simulation results.

Once the best solutions for the three evaluated algorithms were chosen, a test of the performance to varying load conditions was carried out to evaluate the system response for the GWO, PSO, and GA tuned PID controller. In Figure 5 the system response for variable load and variable input voltage condition comparison is shown for each algorithm best solution.

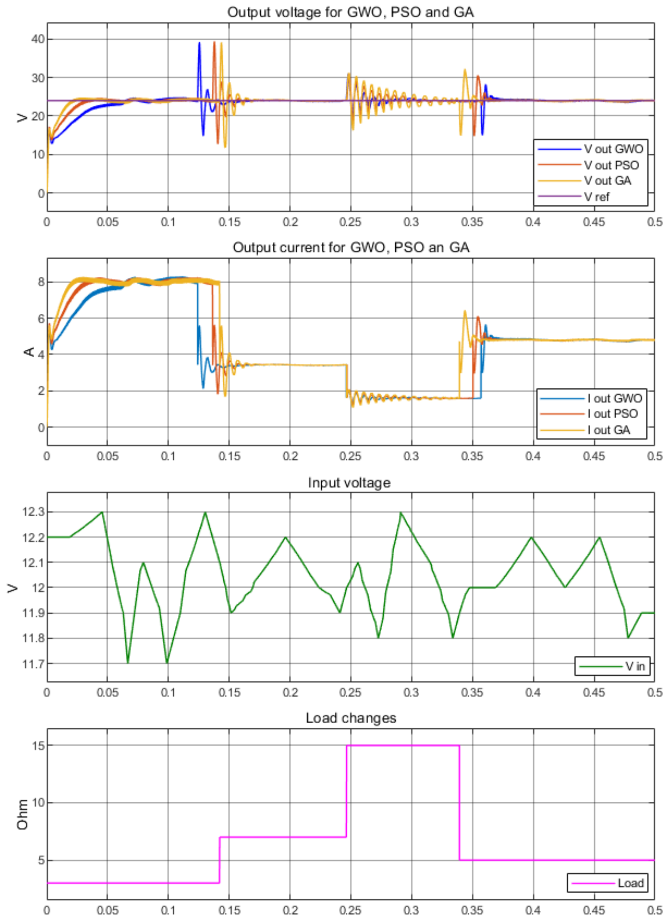

Figure 5: Comparison of system response for (a) output voltage, (b) output current under variable (c) input voltage and (d) load.

As observed in Figure 5, the PID controllers tuned by PSO and GA have similar system responses, presenting important oscillations for load R=15 Ohm. The input voltage to the converter is a signal that varies over time between 11.7 and 12.3 V for the time scale used. The PID controller tuned using the GWO has a better performance to stabilize system response under load and voltage changes in comparison to GA and PSO, despite having a slightly slower response than the other algorithms.

Conclusion

In this paper, the tuning of a PID controller for a boost converter was presented. Three algorithms were implemented and compared for this purpose using MATLAB/Simulink: PSO, GA, and GWO. The power converter is modeled using state-space equations. Several simulations are performed to find optimal values. Results are evaluated using the RMSE and the system response for variable conditions of input voltage and load at the output of the power converter. The GWO-PID tuned controller had the best performance with an RMSE about 50.89% lower than PSO and

44.70% lower than GA. The differences between the obtained RMSE using the three algorithms showed in Table 3, gives insights on the greater susceptibility of PSO and GA to be trapped in local optimum solutions, while the lower RMSE value obtained using the GWO algorithm for the same search space limits indicates that this algorithm manages in a better way to circumvent a greater number of local optimum solutions to find a better optimal solution than the PSO and GA algorithms for this application. After the controller was tuned using each algorithm and the best gain constants were found, the system response was evaluated under input voltage and load changes. The system response for variable load also showed a better performance for the GWO with fewer oscillations for load changes in comparison to PSO and GA. Also, the GWO algorithm had the advantage over the PSO and GA that GWO requires fewer configuration parameters for the optimization process. However, the PID tuned through the GWO was a little slower to reach the reference voltage than the other algorithms. This work gives insights into the GWO algorithm for controller design and control applied to power converters.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

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2.2 Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms

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Solar photovoltaic Maximum Power Point Tracking controller optimization using Grey Wolf Optimizer: A performance comparison between bio-inspired and traditional algorithms

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ABSTRACT

Solar photovoltaic systems are widely used; however, their performance is bound to weather conditions, depending on irradiation, temperature, and the effect of shadows. Maximum Power Point Tracking techniques have been developed to solve this issue. Standard methods use mainly-two algorithms: Perturb and Observe and Incremental Conductance. However, such algorithms perform differently when the Solar photovoltaic system works under sudden solar irradiation changes, temperature, and load changes. This research proposes an optimized Maximum Power Point Tracking controller based on the Grey Wolf Optimization algorithm using the MATLAB/Simulink software as an alternative to the traditional techniques. Global efficiency and Root Mean Square Error evaluate the controller's performance. The response time is analyzed using the Grey Wolf Optimizer algorithm, Wolf Optimizer Algorithm, Simulated Annealing, and Particle Swarm Optimization. These four metaheuristic algorithms are compared to the Perturb and Observe, and Incremental Conductance algorithms. The models are analyzed for the transient state and full-day operation scenarios for constant and variable irradiations, temperatures, and loads. The comparative results show that the Maximum Power Point Tracking controller optimized by the Grey Wolf Optimizer algorithm has superior performance, giving an average 6% output power higher than the other controllers under the test scenarios evaluated. The efficiency of the proposed model was, on average, 3% higher than the Incremental Conductance and Perturb & Observe controllers. For the MPPT controller tunning stage, the Grey Wolf Optimizer Algorithm had the best performance with an RMSE of 255.3549 with a compute time of 27.3 min; the worst performing was the Particle Swarm Optimization with an RMSE of 332.4075 and 27.8 min computation time. The proposed GWO optimized MPPT controller had the faster settling time for each irradiation level compared, with an average of 0.175 s. Also, results showed an improvement of the system response throughout the Maximum Power Point Tracking controller optimized by the Grey Wolf Optimizer algorithm since a lower curling effect is obtained at power converter outputs.

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En esta publicación se realiza una extensión del trabajo previo realizado sobre control primario para convertidores de potencia. Se aplica el algoritmo Grey Wolf Optimizer (GWO) a un controlador Maximum Power Point (MPPT) discreto y acoplado a un arreglo solar fotovoltaico (SFV) para evaluar el desempeño del controlador propuesto contra MPPT basados en técnicas tradicionales ante condiciones ambientales cambiantes. La metodología y resultados se detallan a continuación.

Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms

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Abstract

Solar photovoltaic systems are widely used; however, their performances depend on weather conditions, being affected by irradiation, temperature, and shading. Maximum Power Point Tracking techniques have been developed to solve this issue. This application commonly uses two algorithms: Perturb and Observe and Incremental Conductance. However, these algorithms present an improbable performance when the Solar photovoltaic system works under sudden solar irradiation changes, temperature, and load changes. This research proposes an optimized Maximum Power Point Tracking controller based on the Grey Wolf Optimization algorithm as an alternative to the traditional techniques. The controller's performance is evaluated in terms of global efficiency and Root Mean Square Error, whereas the system response is evaluated using the Grey Wolf Optimizer algorithm, Wolf Optimizer Algorithm, Simulated Annealing, and Particle Swarm Optimization. These four metaheuristic algorithms are compared to the Perturb, Observe, and Incremental Conductance algorithms. The system is implemented and simulated using the MATLAB/Simulink software. The models are analyzed for the transient state and full-day operation scenarios for constant and variable irradiations, temperatures, and loads. The comparative results show that the Maximum Power Point Tracking controller, optimized by the Grey Wolf Optimizer algorithm, has superior performance, giving an output power from the optimized controller with an average of 6% higher than the other controllers under the test scenarios evaluated. The efficiency of the proposed model was, on average, 3% higher than the Incremental Conductance and Perturb and Observe controllers. For the MPPT controller tuning stage, the Grey Wolf Optimizer Algorithm had the best performance with an RMSE of 255.3549 in a compute time of 27.3 minutes, and the worst performing was the Particle Swarm Optimization with an RMSE of 332.4075 and a time of 27.8 minutes. The proposed GWO optimized MPPT controller had the faster settling time for each irradiation level compared, with an average of 0.175 seconds. Also, results showed an improvement of the system response throughout the Maximum Power Point Tracking controller optimized by the Grey Wolf Optimizer algorithm since a lower curling effect is obtained at power converter outputs.

Keywords: Optimization, Metaheuristic Algorithms, Grey Wolf Optimization, Microgrid, Photovoltaic, Maximum Power Point Tracking, Bio-inspired algorithm.

Introduction

Research and implementation of environmentally friendly strategies and Renewable Energy Sources (RES) has become a priority activity at local (Vargas-Salgado, Aparisi-Cerdá, et al., 2022), regional (Vargas-Salgado, Berna-Escriche, Escrivá-Castells, & Alfonso-Solar, 2022; Vargas-Salgado, Berna-Escriche, Escrivá-Castells, & Díaz-Bello, 2022) and global levels (Brodny & Tutak, 2020). Solar energy is usually exploited by Photovoltaic (PV) systems, being attractive due to their relatively low cost, simplicity of installation, little maintenance required, and modularity (Tawalbeh et al., 2021). However, more research is needed to scale up PV systems to improve efficiency and reliability (Victoria et al., 2021). The output power of PV systems depends on weather conditions and the time of day since solar irradiation varies during the day. Due to the varying weather conditions and sudden shading, PV systems are considered nonlinear systems (Liu et al., 2007). Power converters and control techniques have been developed to extract the maximum power from PV systems. For instance, for measured instantaneous current and voltage values, there is a point at which modulation techniques within the corresponding power converter make it possible to extract a maximum of power from the PV system (Dixit et al., 2019). These techniques are known as Maximum Power Point Tracking (MPPT). In addition, to achieve the maximum power extraction from a PV system through the MPPT algorithm, another of its main objectives is to reach that operation point as fast as possible (Sera et al., 2008a) with the minimum number of oscillations in the system response (Jana et al., 2020; Sera et al., 2008b). To implement a MPPT algorithm, a Direct Current to Direct Current (DC-DC) power converter acting as an interface between the PV system and the load is required. Research has been done on comparing the performance of diverse power converter topologies for optimal PV system configurations (Ba et al., 2018).

The MPPT does not refer to a single algorithm; for instance, (Hanzaei et al., 2020) presents a principal scheme-based on a conventional, novel, and hybrid MPPT techniques. Within the traditional MPPT techniques, the most classical approaches are the Perturb & Observe (P&O) (Mohamed Abdelwahab et al., 2020), Incremental Conductance (INC), first proposed in (Wasynczuk, 1983), and hill-climbing in (Ishaque et al., 2014). According to (Eltamaly & Abdelaziz, 2020), these conventional methods are mainly based on the direct measurement of electrical parameters of current and voltage in the PV system and solar irradiation. One of its main advantages is low cost and straightforwardness, as explained in (Motahhir et al., 2020). However, these conventional algorithms have difficulty finding the Global Maximum Peak (GMP) of the MPPT, as is shown in (Ishaque & Salam, 2013).

There are novel MPPT techniques, such as Large and Small Duty Step (LSDS), Large and Mutable Duty Step (LMDS) and Fast and Intelligent GMPPT (FI-GMPPT), whose performance have been demonstrated and validated in (Husain et al., 2019). Nevertheless, their implementation is out of the scope of this study since the main goal is to optimize conventional and widely used MPPT techniques through algorithms.

Considering the complexity and non-linearity of PV systems, conventional MPPT algorithms may fail. Therefore, several novel and hybrid MPPT strategies based on metaheuristics algorithms for intelligent control have been proposed (Rezk et al., 2017). Three main approaches have been applied to the MPPT problem within the bio-inspired algorithms: Artificial Neural Networks (ANN), Fuzzy Logic (FL), and Optimization Algorithms (OA). Current studies compare metaheuristic and classical MPPT methods in PV systems, considering the three main approaches listed above (Naseem, Husain, Minai, et al., 2021).

ANNs have been widely applied in the field of renewable energies since they allow to make predictions of resource availability (Bermejo et al., 2019), estimate operating parameters (Sun et al., 2020), and model nonlinear dynamic renewable energy systems (Chiñas-Palacios, Vargas-Salgado, et al., 2021). A review of different works about the ANN application in MPPT algorithms finds that these algorithms have an average performance of 98% efficiency compared to conventional techniques (Villegas-Mier et al., 2021). In addition to a faster convergence response to the MPPT for uniform operating conditions, constant solar irradiation, ambient temperature, and load; their results are consistent with the results shown in (Jyothy & Sindhu, 2018). While (Farayola et al., 2018) combines an ANN with a fuzzy logic inference engine and a Gaussian vector, the algorithm rapidly converges to the MPPT. Still, the performance of the proposed algorithm is not as expected and presents typical P&O oscillations, possibly due to the insufficient size of the ANN training dataset. Another approach to using ANNs in MPPT systems is to predict input parameters to the controller, for example, cell voltages (Assahout et al., 2018) at different irradiations and temperatures, with real climate conditions such as in (Bouakkaz et al., 2020) and (Attia, 2019) or varying climate conditions (Divyasharon et al., 2019). The work presented in (Nour Ali, 2019) proposes, instead of electrical input parameters to the MPPT controller, to use solar irradiation and temperature as the output of the ANN in the duty cycle for the power converter. (Nour Ali, 2019) show an ANN hybridization approach with a Genetic Algorithm (GA) that allows finding the best topology for ANN, increasing the proposed controller's efficiency. One of the main shortcomings of using an entirely ANN-based approach for a MPPT controller is that the ANN output is limited to the size and quality of the dataset used for its training. Therefore, for different locations of PV systems, a new process of dataset acquisition and training of the ANN would have to be carried out. Optimization algorithms are an alternative to using ANN to find optimal operating parameters for controllers. A clear example is (A. Debnath et al., 2020), as it introduces a novel concept of data arrangement in a Ten Check Algorithm (TCA) in order to develop an Optimized TCA (OTCA), looking for optimization in MPPT for off grid solar PV systems, improving the algorithm speed by 86%. Furthermore, bio-inspired optimization algorithms can find solutions to multidimensional combinatorial problems in nonlinear systems in several fields of applications (Darwish, 2018). These algorithms are based on imitating mechanisms of nature to find solutions to problems or equilibrium (Houssein et al., 2019). They can be based on physical phenomena such as the Simulated Annealing (SA) algorithm, on cosmologic phenomena such as the Multiverse Optimizer (MO), on populations of animal species and their patterns of collective behavior such as the Particle Swarm Optimization (PSO) algorithm, and even on genetic mechanisms such as the GA.

Optimization algorithms are based on exploring a search space limited by the fitness function and the range of possible values for the optimization variables in that function. According to (Ab Wahab et al., 2015) , there are one or more solutions to the stated problem. Optimization algorithms are desirable to find solutions to energy engineering problems related to optimal design (Pérez-Ortiz et al., 2016), where it is sought to maximize or minimize a cost function. The authors in (Aguila-Leon et al., 2020) address the problem of energy exchange between a set of microgrids interconnected using Symbiotic Algorithm Search (SOS) in combination with a game theory approach, and an ANN. The proposed energy management system can exchange energy in an optimal way between microgrids. The authors in (Hayder et al., 2020) present a proposal for a MPPT controller based on a modified version of the PSO; however, when irradiation has sudden changes in short time intervals, the controller exhibits significant output oscillations. Some comparisons have also been made on the performance of various optimization algorithms applied to MPPT controllers; the authors of (Lateef et al., 2020) compare the PSO, Firefly Algorithm (FA), and Modified Firefly Algorithm (MFA) algorithms evaluating the convergence speed and the maximum output power for staggered irradiance conditions at short intervals of time. GA have also been applied to MPPT controllers. For example, in (Mirza, Mansoor, Ling, Khan, et al., 2020) and (Afshan Ilyas, 2018) the authors integrate a PID controller optimized by the GA to find the optimal step size of a Maximum Power Point Tracker Incremental Conductance (MPPT INC) controller. Their results are compared against the P&O algorithm, with the former obtaining a response 56.4% faster with the INC modified by GA than with the P&O, in addition to reduced oscillations in the system response. Also, authors in (A. Debnath et al., 2020) compare a new straight-line approximation based MPP finding algorithm with P&O algorithm concerning: the improvement of the tracking speed, tracking accuracy, maximum power point efficiency and capability to rapid transition, showing that the system reaches the MPP voltage in fewer iterations in fast-changing weathers conditions than the P&O algorithm. As well, the percentage of errors in finding duty cycles and MPPT are much less.

P&O strategies improvement are currently under study. (Ali & Mohamed, 2022) suggests a robust Modified Perturb and Observe (MPO) MPPT algorithm for grid-integrated solar PV systems based on an efficient open-circuit voltage estimation strategy, dividing the PV module curve into four sectors based on the estimated open-circuit voltage. A large step-size perturbation is applied to the two sectors located far from the MPP (to improve the tracking speed) and a small step-size perturbation is applied to the two sectors located close from the MPP (to ensure minimal steady-state oscillations). The results show an enhancement in efficiency tracking and a decrease in the number of sensors, thus reducing its implementation cost.

The authors in (Hadji et al., 2018) also apply a GA algorithm for tuning a PID controller for an MPPT in a wind turbine. The authors in (Azzouz et al., 2019) use a GA algorithm to tune a PID controller for an MPPT in a wind turbine, comparing their proposal against the sliding mode controller. Their results show that the PID controller optimized by GA has a better response than the sliding mode controller, with a faster response.

One of the most significant problems in today's MPPT controllers is the multiple peaks of power at the output of PV arrays due to the bypass of diodes at the output terminal of PV arrays, trying to mitigate the effect of partial shading. This results in traditional algorithms being unable to track the optimal point during partial shading phenomena for multiple peaks corresponding to the different shading pattern on the Power-Voltage (P-V) curve. However, as shown in (Pervez et al., 2021a), the latest nature-inspired algorithms for MPPT have shown encouraging results by preventing convergence to local maximums and resulting in less workload in the processor. Therefore, several authors have worked in this problem, such as authors in (Fares et al., 2021a), in which a comparison of the performance between different bio-inspired algorithms is made: GA, PSO and Squirrel Search Algorithms (SSA), regarding the performance of a MPPT controller under partial shading conditions, aiming to improve a faster tracking time (showed to be 50% faster), to have a faster convergence and fewer power oscillations; achieving a higher efficiency of 99.48 % and an average tracking time of 0.66 seconds. Authors in (Naseem, Husain, Dinesh

Kumar, et al., 2021) also use the PSO approach to test its tracking capabilities under partially shaded conditions; results show that the local maximum is avoided, great efficiency of tracking and consistent and quick tracking speed are achieved. Similarly, authors in (Shams et al., 2021a) seek to improve the MPPT performance using bio-inspired algorithmstaking into account other factors apart from partial shading. They include uniform shading, solar intensity and fast varying load conditions, achieving, after experimental validation, an average tracking time of less than 1 second and even higher efficiencies than previous authors, of 99.85%. Moreover, (Shams et al., 2021c) takes into account same factors, however, using a team game optimization algorithm, which led to great results but not as good as those obtained in the previous article already mentioned with bio-inspired algorithms.

Finally, the authors in (Chiñas-Palacios, Aguila-Leon, et al., 2021) present a novel load management system for smart homes using neural networks and fuzzy logic for load classification, which achieves better scheduling of loads and an intelligent reduction in energy consumption, also adding layers of security to the system through metaheuristic techniques of cryptography for information.

In recent years, a new family of bio-inspired algorithms has emerged; these new optimization algorithms have an advantage over classical PSOs and GAs with a smaller number of adjustment parameters before optimization; this makes them to have a better performance in the exploration of the search space since they are self-adaptive in modifying the search agent's behavior . One of the most recent bio-inspired algorithms that have gained a lot of attention is the Grey Wolf Optimizer (GWO), which imitates the hunting habits of the grey wolf, as shown in (Mirjalili et al., 2014) and (Faris et al., 2018). In works presented in (Aguila-Leon et al., 2020, 2021) the authors show their application for the tuning problem of PID controllers of power converters, comparing their performance against GA, PSO, and classical tuning methods. The results show that the proposed GWO-optimized PID controller has a fast response and low oscillation rates for the system response. An application of GWO to optimize the Fuzzy Logic Controller (FLC) for a solar MPPT controller is shown in (Laxman et al., 2021). The work compares the results to P&O and non-optimized FLC controllers. The optimized FLC controller had a better response under staggered irradiation patterns. Similar test conditions can be found in (Guo et al., 2020). The Whale Optimizer Algorithm (WOA) and the Salp-Swarm Algorithm (SSA) are other recent optimization algorithms. The WOA is based on the whales bubbling net hunting (Gharehchopogh & Gholizadeh, 2019) authors in (Andrić et al., 2019) applied the WOA to solve the solar MPPT problem, comparing the WOA, P&O, and INC MPPT controllers. The SSA is based on the locomotion and habits of salps, marine organisms that form chain-like spiral colonies as they explore the deep ocean looking for food (Mirjalili et al., 2017). Authors in (Mirza, Mansoor, Ling, Yin, et al., 2020) use the SSA to optimize an MPPT controller and compare its performance to

Cuckoo Search (CS) algorithm (Mareli & Twala, 2018; Mosaad et al., 2019), Artificial Bee Colony (ABC) (Agarwal & Yadav, 2019), and Dragonfly Optimization (DFO) (Meraihi et al., 2020); they found an improvement of the power output of the PV array of 8-46% compared to traditional P&O algorithm and 5% greater than the other bio-inspired algorithms used.

To the knowledge of the authors, and according to the bibliography consulted, most of the works presented on optimized MPPT algorithms use ideal conditions of irradiation and temperature; that is, they are constant. Only a few jobs test the controllers against staggered patterns of irradiation and temperature. This research paper presents a discrete PID controller optimized by a GWO algorithm to find the MPPT of a PV system. The main contributions of this work are:

1. A GWO-optimized MPPT based on a discrete-time PID controller is proposed.
2. The performance of the PID controller optimized by GWO is compared against optimizations made with PSO, Simulated Annealing (SA), WOA algorithms, and traditional P&O and INC techniques.
3. The proposed optimized controller model is validated using experimental data of irradiation and temperature under a variable load and a power profile at the power converter output. It is also compared to the power output of an experimental microgrid PV array.

The rest of this manuscript is organized as follows. Section 2 deals with the method regarding electrical models, MPPT control techniques, optimization algorithms and simulation setup; section 3 shows the results and their discussion; and finally, section 4 summarizes the conclusion of this work.

Methods

This research paper proposes an optimized MPPT algorithm using the GWO algorithm as an alternative to traditional INC and P&O techniques. A comparison is made between the MPPT optimized by the proposed algorithm as by other bio-inspired algorithms, as well as by the traditional MPPT techniques of INC and P&O. This section describes the models used, from the PV solar panel to the MPPT power converter, and the different algorithms evaluated for the controller.

Electrical models

This section describes two electrical models: a PV system model and a Boost converter model.

Photovoltaic system model:

A PV system comprises two fundamental parts: the solar module and the solar inverter. Solar modules, typically named solar panels, take advantage of the photoelectric phenomenon to obtain electricity from solar energy. The outputs of a solar module are electric current and voltage, which depend on solar irradiation and ambient temperature. The solar PV array in this paper is modelled using one single diode model. The mathematical expressions commonly used to calculate the PV cell current can be expressed as:

$$I = I_L - I_D - I_{SH} = I_L - I_o \left[\exp\left(\frac{q(V + IR_s)}{nkT} \right) - 1 \right] - \frac{V + IR_s}{R_{SH}} \tag{1}$$

Where q is the charge of the electron; K is the Boltzmann constant; T is the absolute temperature of the P–N junction; V is the diode voltage; n is an ideal factor; R_S is the series resistance; R_{SH} is the parallel resistances; I_o is the saturated reverse current; I_L is the current obtained directly from the sun; I_D is the diode current; I_{SH} is the parallel branch current and I is the cell's current. Therefore, the output current of the solar cell generated by the PV module can be modelled as:

$$I_{os} = I_{or} \left(\frac{T}{Tr} \right)^3 \cdot \left[\exp\left(\frac{qE_{GO}}{\beta k} \right) \cdot \left(\frac{1}{Tr} - \frac{1}{T} \right) \right] \tag{2}$$

$$I_{sol} = I_{SC} K_i (T - 298.18) \frac{\lambda}{1{,}000} \tag{3}$$

In (2), I_{os} refers to the reverse saturation current of the diode, I_{or} is the saturation current at Tr, where Tr is the reference temperature in Kelvin (K), T denotes the temperature in K, q is the electron charge ($1.6022\ x\ 10^{-19}$ C), E_{GO} implies the bandgap energy at T = 0 K, β expresses an idealistic factor in the diode, k refers the Boltzmann's constant ($1.3806\ x\ 10^{-23}\ \frac{J}{K}$). Additionally, for the calculation of the solar cell output current (I_{sol}), in (3) I_{SC} indicates the short circuit current, K_i denotes the temperature constant at I_{SC}, and λ represents the solar radiation ($\frac{W}{m^2}$).

Boost converter model:

The boost converter used for the MPPT is modelled using state-space equations and is simulated by the MATLAB/Simulink software. Using Kirchhoff's voltage and current laws analysis to obtain the state-space equations for each system determined by the activation/deactivation of the Metal-Oxide-Silicon Field-Effect-Transistor (MOSFET) with the u control signal value. For u, the signal can be represented as a Boolean value (true 1, false 0). Therefore, there are two possible combinations for the electric configurations of the Boost converter, i. e. charge and discharge cycles for the L and C elements. These combinations are summarized in a single matrix form of state-space equations shown in (4).

$$\begin{bmatrix} \frac{dv_o(t)}{dt} \\ \frac{di_L(t)}{dt} \end{bmatrix} = \begin{bmatrix} \frac{1-u}{C} & -\frac{1}{CR} \\ 0 & -\frac{1-u}{L} \end{bmatrix} \begin{bmatrix} v_o(t) \\ i_L(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{L} \end{bmatrix} v_i(t) \tag{4}$$

Where $v_o(t)$ is the output voltage, u is the control signal of the Pulse-Width Modulation (PWM) generated by the PID controller, C is the capacitance value, R is the resistance value, $v_i(t)$ is the input voltage of the boost converter, $i_L(t)$ is the inductor's current and L is the inductance value.

Maximum Power Point Tracker techniques

In this section, the MPPT techniques are analyzed, compared are described.

***Perturb & Observe based Maximum Power Point Tracking**:*

The P&O algorithm is the most common application for a PV generator due to the simple implementation, structure, and few set-up parameters. This method is based on the instantaneous measurement of voltage and current delivered by the PV module. This technique introduces a minor perturbation to cause a power variation in the PV module. The PV output power is measured and compared constantly with the previous power. An increase in the PV voltage will lead to an increase in the output power. Hence, a perturbation is needed to observe the behavior of the output power to reach the maximum value of the MPPT. It requires a power-voltage ratio $\left(\frac{\Delta P}{\Delta V}\right)$ variation stat. To summarize this, Figure 1 shows the flowchart of the P&O algorithm for the MPPT.

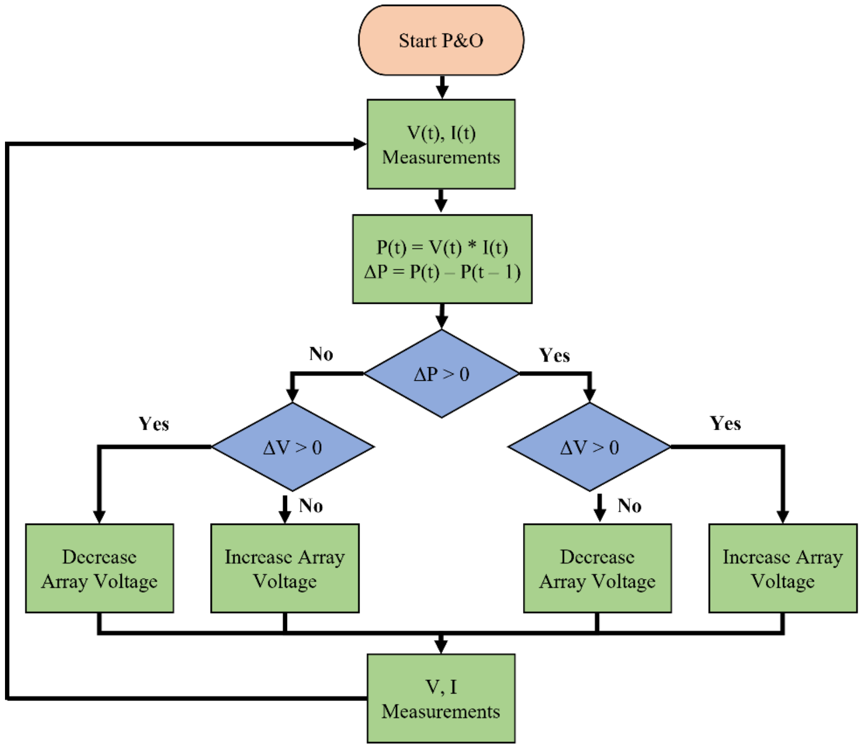


Figure 1. Flowchart of P&O method for the MPPT of the voltage reference.

Incremental Conductance based Maximum Power Point Tracking:

The INC algorithm controller is based on measuring incremental changes of voltage and current in the PV array. Because of this, the controller requires more computational time to perform the calculations, although it has more accuracy and best voltage tracking than the P&O. This technique uses the incremental conductance $\left(\frac{\Delta I}{\Delta V}\right)$ of the PV array to calculate the sign of the variation in terms of power with respect to the voltage $\left(\frac{\Delta P}{\Delta V}\right)$. The INC algorithm performs the calculation of the MPPT by comparing the incremental inductance with the array conductance $\left(\frac{I}{V}\right)$. When $\left(\frac{\Delta I}{\Delta V}\right)$ and $\left(\frac{I}{V}\right)$ are the same, the output voltage is the MPPT voltage. The representative equations of the INC algorithm are expressed by equations (5-7).

$$P = V \cdot I \tag{5}$$

$$\frac{\Delta P}{\Delta V} = \frac{\Delta (VI)}{\Delta V} = \frac{V \Delta I}{\Delta V} + \frac{I \Delta V}{\Delta V} = \frac{V \Delta I}{\Delta V} + I \tag{6}$$

$$\left(\frac{1}{V}\right)\frac{\Delta P}{\Delta V} = \left(\frac{1}{V}\right)\frac{V \Delta I}{\Delta V} + I\left(\frac{1}{V}\right) \tag{7}$$

The main task of this algorithm is to search for the voltage operating point at which the incremental conductance is the conductance $\left(\frac{\Delta I}{\Delta V} = \frac{I}{V}\right)$. The controller preserves the voltage until the irradiation value changes and the process repeats it again. The flowchart of the INC is shown in

Figure 2.

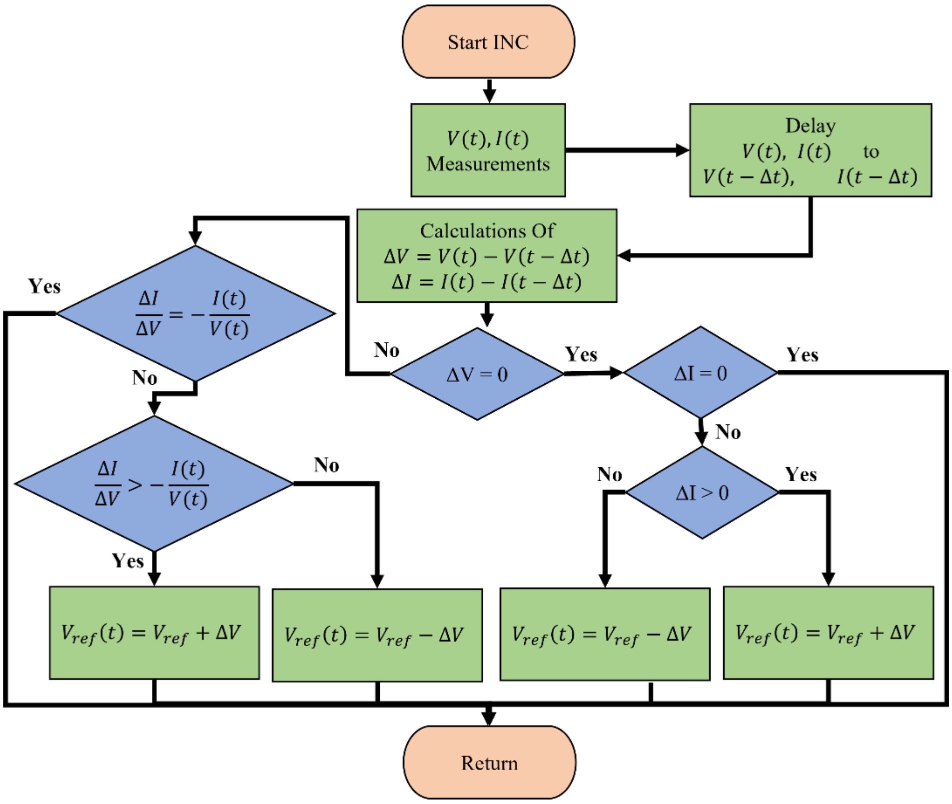


Figure 2. Flowchart of the INC algorithm.

Proposed Optimized Grey Wolf Optimizer Discrete-Proportional-Integral-Derivative Maximum Power Point Tracking Controller:

PID controllers are widely used in industry, despite being first proposed more than seventy years ago. They currently make up about 95% of the controllers installed (Podržaj, 2018) in various industrial applications. PID controllers have an advantage over other types of controllers in that their physical implementation is well developed and extended.

For the correct operation of PID controllers, it is necessary to tune them to find the correct values of proportional, integral and derivative gain. It is reported that about 25% of installed PID controllers in the industry are currently tuned according to the plant on which they operate (Yu, 2006). There is an opportunity to improve the correct tuning of the controller through novel methods, such as tuning through FL (D. Mohanty & Panda, 2020), OA (Fan et al., 2019) and ANN (M. K. Debnath et al., 2020). Novel methods differ from classical methods by providing controllers a wider range of marginal operation by not relying on classical graphical or mathematical methods for the determination of K_p, K_i and K_d gains. The literature has explored options of tuning PID controllers using the modern methods mentioned above. However, little attention has been paid to the fact that most PID controllers installed in the industry are essentially discrete-time controllers (as digital electronics implement them); thus, in this work, the tuning of a PID controller in discrete time to be integrated into an MPPT controller is proposed. The equation of a PID controller in continuous time is defined according to (8).

$$u(t) = K_p\left[exp(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{d}{dt}exp(t)\right] \tag{8}$$

Where $u(t)$ is the control signal, K_p is the proportional gain, $e(t)$ is the error signal between a reference signal and the system response, T_i is the integration time and T_d is the derivative time. Currently, PID controllers are implemented by digital electronics devices and therefore the signals they handle are discrete.

In this work, the proposed MPPT controller is based on a discrete-time PID controller capable of addressing the non-linearity of the variant conditions of its operation for solar PV applications. A nonlinear discrete-time PID controller is proposed; non-linearity is achieved by making the error's integral part of the nonlinear function. The forward Euler method converts the analog PID controller to a discrete PID controller. The resulting equation for a nonlinear discrete-time PID controller is presented in (9).

$$U(z) = E(z)\left[K_p + K_i\frac{T_s z}{z-1} + K_d\frac{N(z-1)}{(1+NT_s)z-1}\right] \tag{9}$$

The PID controller tries to reduce the error signal E(z) shown in (26); such reduction depends on the values assigned to the proportional gain K_p, integral gain K_i, derivative gain K_d, and N (derivative filtering coefficient). The proposed nonlinear discrete PID MPPT controller is integrated into the PV system as shown in Figure 3.

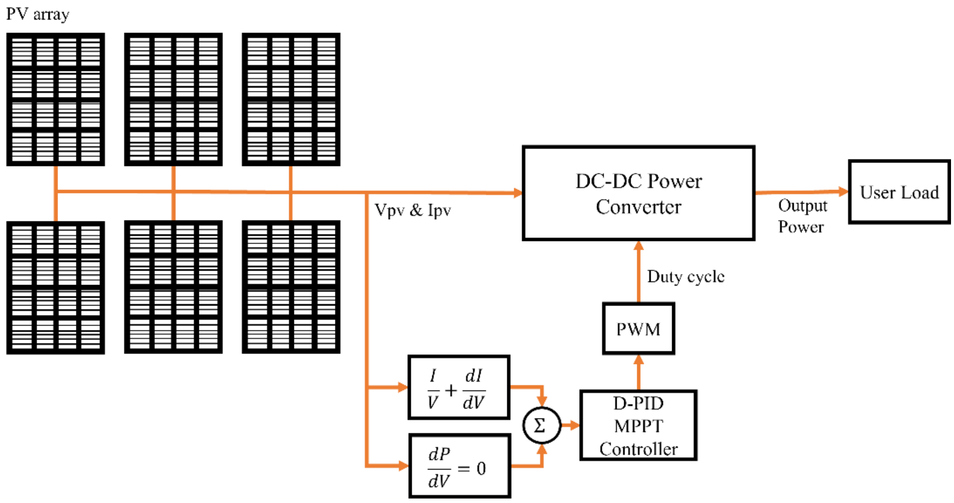


Figure 3. Overall diagram of the proposed MPPT controller integration to system.

The proposed discrete-time PID controller is based on the method of incremental conductance and instantaneous conductance. It tries to reduce the error between the output power differential and the voltage, since the tangent slope characteristic in the P- V curve is zero in MPPTs based on incremental conductance. In continuous time, the calculations for the proposed controller's reference and error performed by (10) according to the work of (Kamalakannan et al., 2014).

$$\frac{dP}{dV} = \frac{d(VI)}{dV} = I + V\frac{dI}{dV} = 0 \tag{10}$$

To reduce the error signal from equation (26), it is necessary to tune the controller, that is, to find the ideal combination of the gains of the controller. The proposed controller has been tuned using four optimization algorithms: GWO, PSO, SA, and WOA. Answers obtained by these algorithms are compared to determine which of them has the best performance; they are also compared with the typical algorithms of P&O and INC performance. To perform optimization of any problem is essential to determine the objective function and the optimization variables. The selected objective function is the reduction of error E(z) by evaluating it in terms of the Root Mean Squared Error (RMSE), according to (11).

$$RMSE = \sqrt{\frac{\sum_{n=0}^{T_{sim}} \left(y_{out}[k] - y_{ref}[k]\right)^2}{T_{sim}}} \tag{11}$$

Where T_{sim} is the total simulation time, n is the current measurement, $y_{out}[k]$ is the measurement of the power output of the boost converter, and $y_{ref}[k]$ is the reference of the proposed controller.

In a MPPT controller, the gains and filtering coefficients of its related PID controller are important, as well as the operating parameters of the PWM that the control signal will generate for the power converter. The vector of optimization variables of the proposed controller is shown in (12).

$$\bar{X} = [K_p \quad K_i \quad K_d \quad N \quad f] \tag{12}$$

Where, $\bar{X}$ is the vector of variables to optimize, K_p is the proportional gain of the controller, K_i is its integral gain, K_d is its derivative gain, N is the derivative filtering coefficient, and f is the frequency of operation of the PWM module that modifies the duty cycle of the boost converter.

Once the objective function, the optimization variables, and their limits are defined, the controller is tuned using the proposed metaheuristic algorithms. Figure 4 shows the methodology followed to optimize the proposed controller in this work.

As seen in Figure 4, the methodology followed for optimizing the proposed controller and its performance validation is divided into three main stages. The input data is collected in the first stage using a weather station and a power meter. In the second stage, the data is entered into the model of the PV solar array, from where voltages and currents are obtained; in this same stage, the optimization is carried out in parallel for each of the metaheuristic algorithms. After the optimization iterations have ended, each algorithm returns a vector of optimized variables $\bar{X}_{best}$ and its corresponding RMSE. Finally, in stage 3, all the controllers are compared, both optimized by metaheuristic algorithms, by MPPT INC and by P&O algorithms. In this stage, the performance of all the algorithms is evaluated under different operating scenarios detailed in the section of simulation conditions and results of this work.

One of the scopes of this research is to select the best OA for the proposed MPPT controller, making a comparative analysis between GWO, PSO, SA, and WOA, as an alternative to traditional INC and P&O MPPT techniques. A brief description of each OA implemented is explained in the following sections.

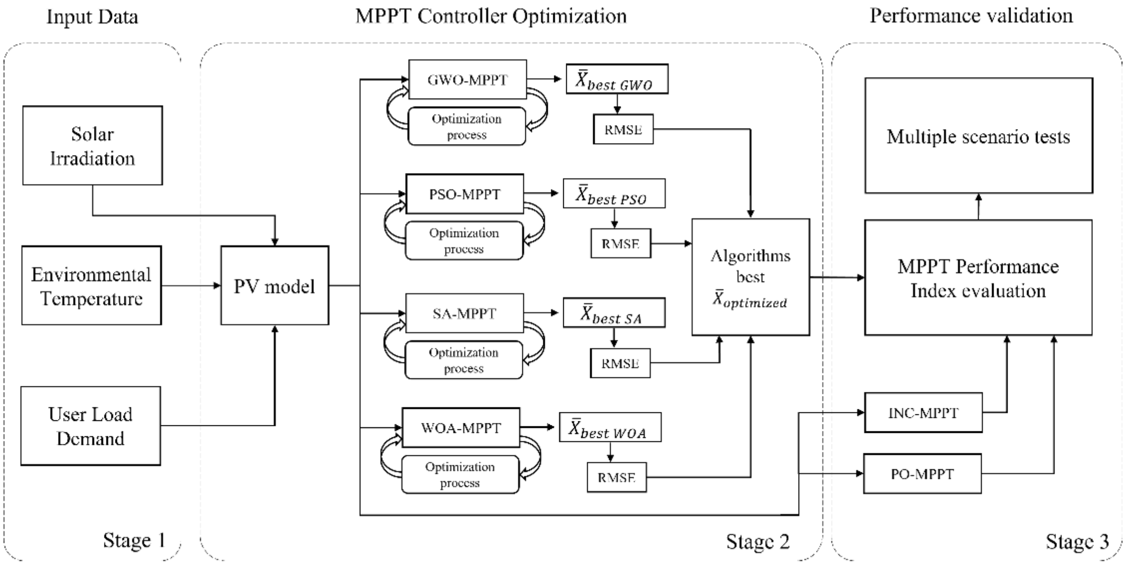


Figure 4. Overall diagram of the methodology for the proposed optimized MPPT controller.

Optimization Algorithms

Grey Wolf Optimizer

The GWO algorithm mimics the natural hunting behavior of grey wolves. In every herd of wolves, the tasks performed by each role are classified hierarchically as a leading wolf, called alpha (α) wolf, secondary wolves and beta (β) wolves, as well as those wolves which are subordinated to the alpha and beta wolves are called delta (δ) wolves, and finally, supported wolves are omega (ω) wolves. There are three main stages in the hunting process of grey wolves in nature: encircling, hunting, and attacking.

Encircling stage: In this stage, each wolf updates its position in the search space according to the relative best position to prey, stated for α wolf. The encircling behavior of the prey is modeled mathematically by (13-16).

$$\vec{X}(t+1) = \vec{X}_{pos}(t) - \vec{A}\vec{D} \tag{13}$$

$$\vec{A} = 2ar_1 - a \tag{14}$$

$$\vec{C} = 2r_2 \tag{15}$$

$$\vec{D} = \left|\vec{C}\vec{X}_{pos}(t) - \vec{X}(t)\right| \tag{16}$$

Where $\vec{A}$ and $\vec{C}$ are vectors of coefficients, $\vec{X}_{pos}$ vector of the position of the prey, $\vec{X}$ vector of the position of the wolf, t is the current iteration, r_1 and r_2 are values randomly generated between zero and one, and vector a is a value decreases linearly as it iterates.

Hunting stage: The position of wolves is reorganized according to their proximity to the prey. The wolf with the nearest distance to the prey is assigned to be the alpha α wolf, β, and δ wolves according to their distance, from least to greatest. Equations (17-19) describe the wolve position updating.

$$\vec{X}_i(t+1) = \frac{\vec{X}_{i1} + \vec{X}_{i2} + \vec{X}_{i3}}{3} \tag{17}$$

$$\left.\begin{aligned} \vec{X}_{i1} &= \vec{X}_\alpha(t) - \vec{A}_1\vec{D}_\alpha \\ \vec{X}_{i2} &= \vec{X}_\beta(t) - \vec{A}_2\vec{D}_\beta \\ \vec{X}_{i3} &= \vec{X}_\delta(t) - \vec{A}_3\vec{D}_\delta \end{aligned}\right\} \tag{18}$$

$$\left.\begin{aligned} \vec{D}_\alpha &= \left|C_1\vec{X}_\alpha(t) - \vec{X}_i(t)\right| \\ \vec{D}_\beta &= \left|C_2\vec{X}_\beta(t) - \vec{X}_i(t)\right| \\ \vec{D}_\delta &= \left|C_3\vec{X}_\delta(t) - \vec{X}_i(t)\right| \end{aligned}\right\} \tag{19}$$

Where $\vec{X}_i(t+1)$ is the wolf with the best position to the prey and i is the current iteration number of the GWO algorithm.

Attack stage: Attack to prey arises when the herd is over the prey. Minimizing the distance between the wolves and the prey in this stage is necessary. The prey is considered the best global solution. For this reason, it must be defined as a vector A to make a decreasing coefficient dependent on the iteration number. The vector A value is reduced as the value index a is reduced according to (20). Figure 5 shows the GWO algorithm flowchart.

$$a = 2 - t\left(\frac{2}{T}\right) \tag{20}$$

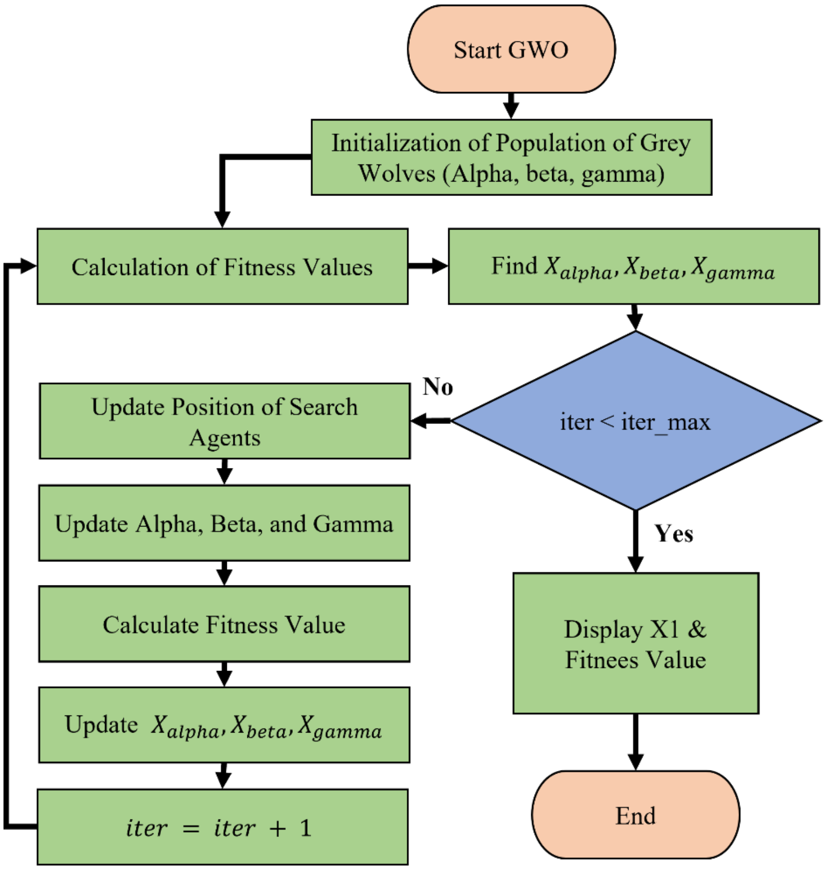


Figure 5. Flowchart of the GWO algorithm.

Particle Swarm Optimization

The PSO algorithm mimics the swarm behavior of certain species of animals for hunting, foraging for food or building a place for rest. This algorithm's collectiveness is the essence, especially because each search agent must be represented in a mathematical model for the PSO. Due to this, the search agents are the particles of a swarm, considering their position within the exploration space, velocity, and acceleration rates. In the initialization of the PSO, many particles are randomly set up into a search space where the global solution for the optimization problem is within. To find a global solution rest on the evaluation and minimization of the objective function. To converge into a global solution, the particles must be updated iteration by iteration in their positions, velocities, and accelerations. A fitness function is mathematically evaluated for each particle. The best value acquired for the fitness function of the whole particles is called the best global g_{best}. Throughout the iteration process, each best value of the particle fitness function is called the personal best p_{best}. At each complete iteration, the speeds of the particles accelerate on the way to the best global solution and the best personal according to (21).

$$v_n = w * v_n + c_1 rand() * (g_{best,n} - x_n) + c_2 rand() * (p_{best,n} - x_n) \qquad (21)$$

Where v_n is the speed update of the particles, w is a factor of inertia whose value is decreased from 0.9 to 0.4 overtime, c_1 and c_2 are coefficients of acceleration pointing to the best global and the best personal. Figure 7 shows the flowchart of the PSO algorithm.

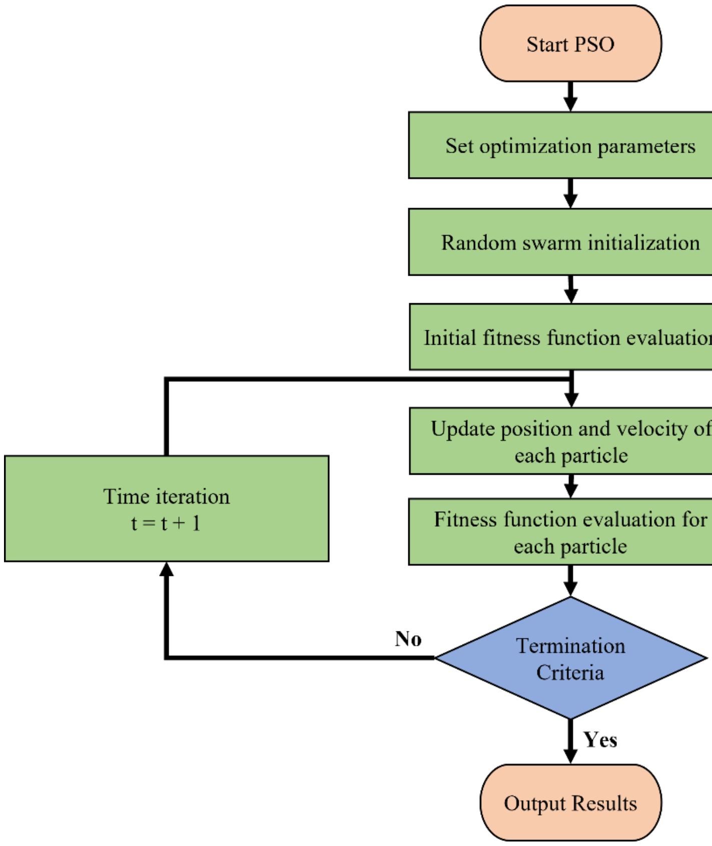


Figure 6. Flowchart of PSO algorithm.

Simulated Annealing

The SA algorithm is a stochastic approach that simulates the statistical process of growing crystals using the annealing process to reach its absolute (global) minimum internal energy configuration. If the temperature in the annealing process is not lowered slowly and enough time is not spent at each temperature, the process could get trapped in a minimum local state for the internal energy. The resulting crystal may have many defects, or the material may even become glass with no crystalline order. The simulated annealing method for the optimization of systems emulates this process. Given a long enough time to run, an algorithm based on this concept finds global minima for continuous-discrete-integer variable nonlinear programming problems.

The basic procedure for implementing this analogy to the annealing process is to generate random points of the current best point and evaluate the problem functions. If the cost function (penalty function for constrained problems) value is smaller than its current best value, then the point is accepted, and the best function value is updated. If the function value is higher than the best value known thus far, then the point is sometimes accepted and sometimes rejected. Point's acceptance is based on the value of the probability density function of the Boltzmann-Gibbs distribution. Suppose this probability density function has a value greater than a random number. In that case, the trial point is accepted as the best solution even if its function value is higher than the known best value. Figure 7 shows the flowchart of the SA algorithm.

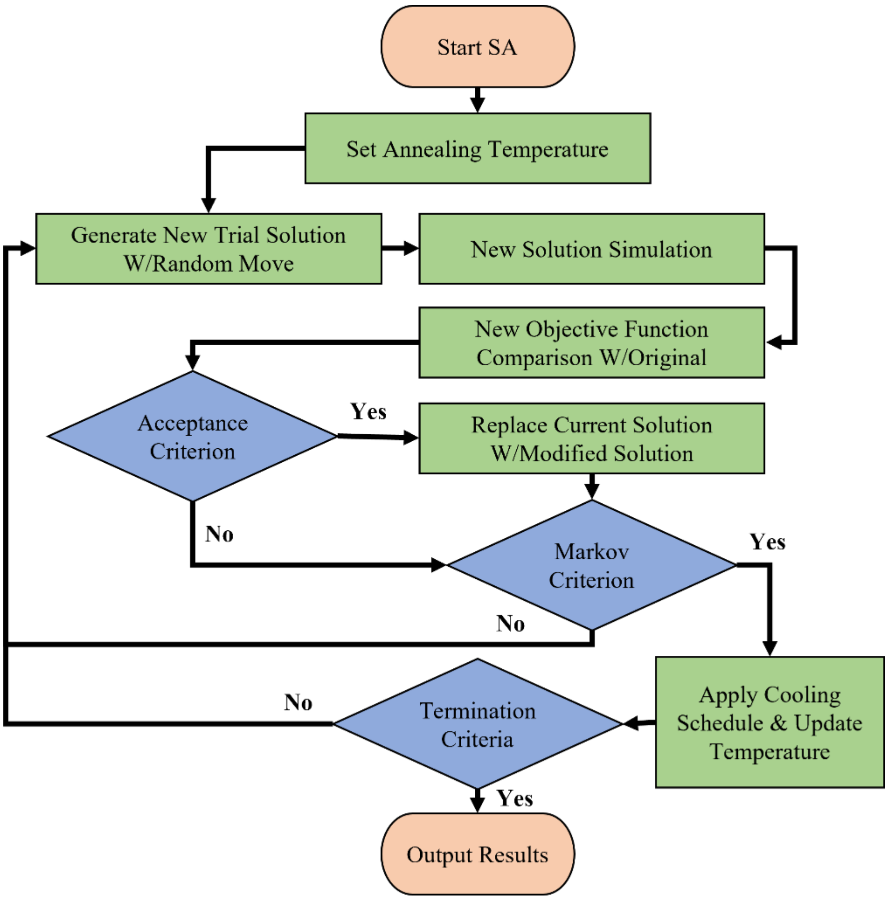


Figure 7. Flowchart of SA algorithm.

Whale Optimization Algorithm

Mirjalili et al. (Mirjalili & Lewis, 2016) developed a new stochastic population algorithm named Whale Optimization Algorithm. The humpback whales' social behavior is behind this algorithm's inspiration(Abderrahim et al., 2021). More directly, the WOA is a mimic of the bubbles net feeding in the foraging behavior of humpback whales.

Two main phases are required to compose the algorithm: the exploitation phase (which contains two steps: the encircling prey and the bubble-net attacking) and the exploration phase (which consists of searching for prey). In the following section, it is described the mathematical model of WOA.

Exploitation phase (encircling prey, bubble -net attacking):

The mathematical model of the encircling behavior of the humpback whales is given in (21) and (22).

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X'}(t) - \vec{X}(t)\right| \tag{21}$$

$$\overrightarrow{X'}(t+1) = \overrightarrow{X'} - \vec{A} \cdot \vec{D} \tag{22}$$

Where t indicates the current iteration, X' represents the best solution obtained so far, X is the position vector. Equations (23) and (24) are used to calculate the coefficient vectors A and C.

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \tag{23}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{24}$$

Where a decrease linearly from 2 to 0 over-the course of iterations (in both exploration and exploitation phases) and r is a random vector generated with uniform distribution in the interval of [0,1]. Search agents update their positions based on the best-known solution. The solution location is controlled by the adjustments of A and C values. The humpback hunting method is based on shrinking encircling mechanism and a spiral trajectory towards the prey. The shrinking behavior is formulated by (25).

$$a = 2 \qquad t\frac{2}{MaxIter} \tag{25}$$

Where t is the iteration number and $MaxIter$ is the maximum number of allowed iterations. The distance between the actual solution and the best position is used to calculate the spiral-shaped path, as represented in (26).

$$\vec{X}(t+1) = D' \cdot \exp(bl) \cdot cos(2\pi) + \overrightarrow{X'}(t) \tag{26}$$

Where $D' = \left|\overrightarrow{X'}(t) - \vec{X}(t)\right|$. The distance of the whale from the prey (the best solution obtained so far) is described by (21). To choose between the two mechanisms (shrinking encircling mechanism and the spiral-shaped path) with probability of 50% during the optimization process, a random coefficient is included as p in $[0,1]$. The shrinking encircling is used to update the position when $p < 0{,}5$. The spiral-shaped path is used elsewhere.

Exploration phase (search for prey):

When whales create a bubble-network, they have a certain probability of searching for prey. Mathematically, the search for prey will enhance the WOA exploration. In this phase, coefficient A must change. The distance data D is randomly updated if A exceeds the range of [-1,1]. At this moment, the algorithm has a certain global search ability since whales deviate from the original optimal fitness, represented in (27) and (28).

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{rand} - \vec{X}\right| \tag{27}$$

$$X(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{28}$$

Where, X_{rand} is the random location information of a whale selected from this iteration. Figure 8 depicts the flowchart of WOA technique.

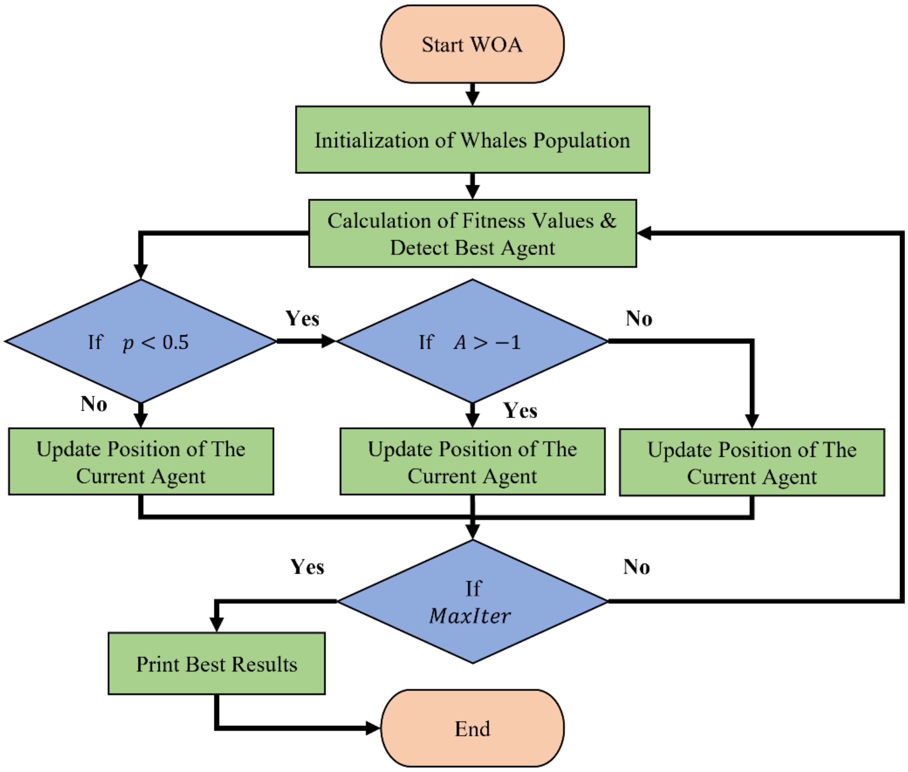
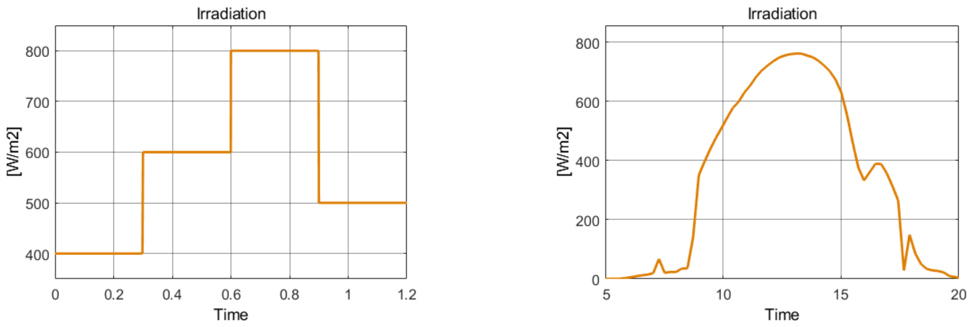


Figure 8. Flowchart of WOA.

Simulation conditions

Finally, after implementing the different algorithms in the models, the simulation of the system is carried out to obtain key performance indicators for each of them. This section describes the simulation conditions that were implemented. The proposed MPPT optimized model was evaluated under four different scenarios. The irradiation and temperature data used are real. They correspond to measurements made on June 7, 2019, in the Renewable Energy Laboratory (LabDER) of the Universitat Politècnica de València, Spain. The evaluated scenarios are: scenario 1 with constant load and temperature with staggered irradiation, scenario 2 with variable load and temperature with staggered irradiation, scenario 3 considers constant load and temperature with variable irradiation, and scenario 4 under variable load and temperature with variable irradiation. The constant values for scenarios 1 and 3 are 25 °C degrees for the ambient temperature and 96 Ohm for the load impedance value.

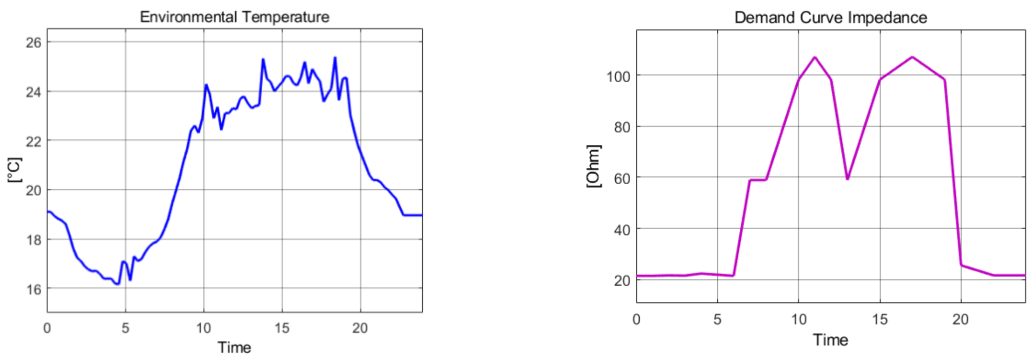
The staggered solar irradiation profile is shown in Figure 9(a) used for scenarios 1 and 2. Figure 9(b) shows the real irradiation profile used for scenarios 3 and 4. As can be seen in Figure 9(b), the irradiation profile used is from the actual measurements of a day, with significant fluctuations due to the cloudiness of the city of Valencia in the months of June and July. These conditions cause a partial shading effect over all the solar panel array since rapid solar irradiation changes are evaluated.



(a) (b)

Figure 9. Solar irradiation profile; (a) staggered solar irradiation profile for scenarios 1 and 2 and (b) real solar irradiation profile for scenarios 3 and 4.

Scenarios 3 and 4 are intended to evaluate the performance of the PV array system under more realistic operation conditions. Scenario 3 uses a real irradiation curve to keep temperature and load constants. In scenario 4, solar irradiation, environmental, and load profiles are variables from real data. Figure 10(a) shows the environmental temperature and Figure 10(b) shows the load impedance profiles used in this work for varying conditions.



(a) (b)

Figure 10. (a) Environmental temperature profile and (b) load impedance profile used for variable conditions scenarios.

The MPPT controller is based on a boost converter to extract the maximum possible power from the PV array according to each MPPT algorithm. In Table 1, the configuration of the MPPT controller boost converter is shown.

Table 1. Boost converter parameters

Description	Value
Coupling capacitor	26.0000 μF
Power converter capacitor	26.0000 μF
Inductor	01.0224 μH
Input voltage	0 – 600 V
Load impedance	0 – 100 Ω

For the simulation and evaluation tests of the different proposed algorithms, the installation of photovoltaic panels of the LabDER was considered. Figure 11 shows the PV and IV curves of the PV array.

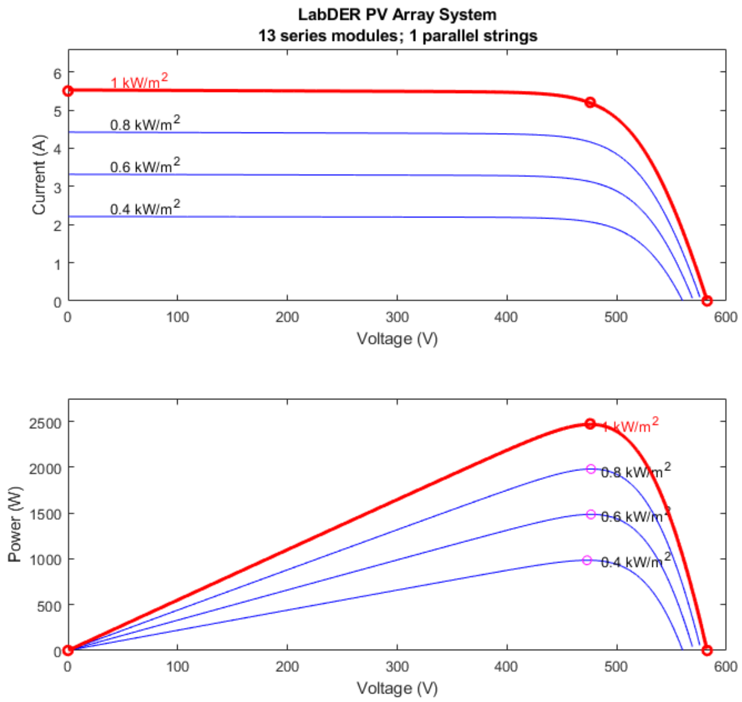


Figure 11. PV and IV curves of the PV array considered for the evaluation of MPPT controller algorithms.

The following section shows the performance results for the MPPT controller by using different control algorithms and tuning methods.

Results

The results obtained from this research work have been divided into two parts; the first part details the results on the optimization of the proposed PID-discrete MPPT controller, optimized by different algorithms; the second part of the results focuses on the comparative study of the performance of the different MPPT controllers considered for the different test scenarios described in the previous section.

Optimized Grey Wolf Optimizer Discrete-Proportional-Integral-Derivative Maximum Power Point Tracking controller:

The GWO, WOA, SA, and PSO algorithms were implemented using MATLAB/Simulink to validate their performance in tuning a MPPT controller against the commonly used P&O and INC MPPT controller algorithms. For each algorithm, tuning was divided into two stages: (a) initial exploration, where the search space for each variable was vast and (b) refined search around the best solution obtained in the first stage to discard better optimal solutions near the one previously found. Table 2 summarizes all the configuration parameters considered for each optimization algorithm evaluated in this work to optimize the proposed MPPT controller.

Table 2. Optimization algorithm configuration parameters.

	Parameters	
Algorithm	Description	Values
GWO	Wolves number	12
	Maximum iterations	5
PSO	Particle number	50
	Inertia factor	0.4-0.9
	Self-adjustment weight	3
	Social-adjustment weight	1
	Maximum iterations	7
SA	Tolerance	1e-2
	Initial temperature	100
	Maximum function evaluations	10
	Maximum iterations	7
WOA	Whales number	12
	Maximum iterations	5

Depending on the type, optimization algorithms require different configuration parameters prior to their use. The setting of these parameters modifies the speed and the accuracy of the response obtained in the optimization problem. That is why the more tuning parameters an algorithm that there are, the less fast or accurate it is likely to be. The GWO and WOA algorithms used in this work have an advantage over other optimization algorithms as they have few parameters to adjust.

In addition to the adjustments of the optimization parameters for the different algorithms, it is necessary to specify the search space limits. Table 3 summarizes the minimum and maximum limits for each considered variable.

Table 3. Summary of maximum and minimum values for optimization variables and parameters

Variable / Parameter	Limit
K_p	0-100
K_i	0-200
K_d	0-5
N	0-15
F	0-10,000
D	0.05-0.978

After several simulations, each bio-inspired algorithm found the best combination of K_p, K_i, K_i, N and F. The obtained values for the optimization variable vector are then used in the related MPPT controller to evaluate the system under different scenarios. Table 4 shows the summary of the results obtained by the optimization algorithms.

Table 4. Optimization algorithm results summary.

5Parameter	Algorithm			
	GWO	PSO	SA	WOA
K_p	5e-4	0.3445	8.1913e-4	5e-4
K_i	12.0761	11.3564	32.9626	8.0070
K_d	5e-4	0.0725	8.1916e-4	5e-4
N	2.5237	8.1126	10.3338	1.8691
F	4000	5324.7	6031	4123
$Best\ Score\ *$	255.3549	332.4075	267.4116	257.2519
Simulation time (s)	1637.57	1669.41	629.48	181002

* Based on RMSE value.

As shown in Table 4, the results of the bio-inspired algorithms have similarities. After several simulations in the four optimization algorithms, it was found that the GWO algorithm had the best score, with an RMSE of 255.3549. It is remarkable how the results of the GWO and the WOA are very close to each other, especially in terms of the constants K_p, K_i and the frequency F of the PWM generator, even the RMSE between both algorithms is similar. However, the computational time of the WOA is more than 100 times higher than that required by the GWO to find the solution. The fastest algorithm to find the solution to the tuning problem of the MPPT controller was the SA; however, its RMSE was 267.4116, which is 4.7% higher than the RMSE of the GWO, of 255.3549. The RMSE obtained by the GWO, SA and WOA algorithms are in similar ranges, with the three algorithms having an average RMSE of 260.0005.

The worst performing bio-inspired algorithm was the PSO algorithm, with a RMSE 27.8% higher than the average of the other three algorithms. The speed with which the algorithms find the best possible solution is plotted by a convergence curve that indicates the evolution of the algorithm's score, measured in terms of the RMSE, and the iteration number. Figure 12 shows the convergence curves of the evaluated algorithms.

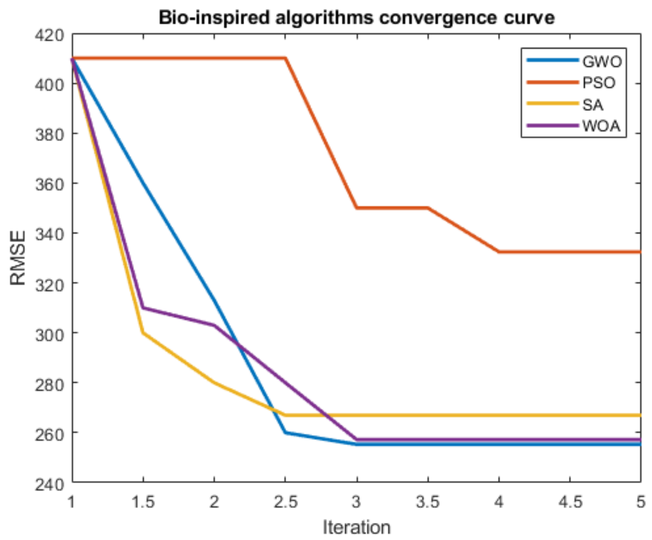


Figure 12. Convergence curve plot for the bio-inspired algorithms evaluated for the proposed PID MPPT controller.

As shown in Figure 12, the PSO algorithm remains far from the best solutions found by the GWO, the SA, and the WOA algorithms. It is remarkable how quickly the SA finds its best solution, being the fastest and with the lowest number of iterations, without having apparent changes after 2.5 iterations. The convergence curves in Figure 12 give indications not only of how fast an algorithm finds the best solution but also give information about how long an algorithm stays stuck in a local optimum; local optimums occur when the slope of the convergence curve is equal to zero, as observed from iteration 1 to 3 for the case of PSO, and then from 3 to 3.5 in the same algorithm. Both the GWO and the WOA come up with their best solution at the third iteration; however, the WOA has a higher error than the GWO, and as shown in Table 8, it is a very slow algorithm for this application. The results obtained by the PSO compared to the other algorithms is consistent with the fact that the PSO needs to have an optimal performance, needs to be previously adjusted by an expert who understands the behavior of the algorithms for a specific application, which makes it inefficient at times. The convergence speed of the SA is remarkable; this can be explained because it is based on a relatively simple physical phenomenon compared to social particle algorithms, such as GWO and WOA. The results obtained by the PSO compared to the other algorithms is consistent with the fact that the PSO needs, to have optimal performance, to be previously adjusted by an expert who knows very well the behavior of the algorithms for a specific application which makes it inefficient at times. The convergence speed of the SA is remarkable; this can be explained because it is based on a relatively simple physical phenomenon compared to social particle algorithms, such as GWO and WOA. The minimum duty cycle value configured for the algorithms was 0.05 and the maximum was 0.978. For large values of change in the duty cycle, a greater oscillation in the response of the system was observed, which is consistent with the authors' findings (Angadi et al., 2021; Husain & Tariq, 2018). To avoid undesirable output oscillations the duty cycle step size was configured to 0.001.

MPPT controller performance comparison

After tuning the discrete PID MPPT controller, a comparison was made between this controller, tuned by various bio-inspired algorithms, and the P&O and INC MPPT controllers commonly used in industry. To validate the results of the proposed controller, an evaluation of a 2.1 kW PV system output was made for the different MPPT controllers considered. The summary of results for each evaluated case can be observed in Table 5.

Table 5. Performance index summary for each evaluated case.

		Index			
Scenario	**MPPT algorithm**	**RMSE**	**Mean efficiency**	**Maximum PV output power (W)**	**Generated Energy (Wh)**
1	GWO	88.53	0.662	1821.7	1209.1
	PSO	207.92	0.609	1543.1	1023.5
	SA	152.85	0.649	1645.4	1091.3
	WOA	106.94	0.648	1750.9	1161.3
	INC	160.02	0.644	1752.4	1165.0
	P&O	120.02	0.642	1714.1	1137.3
	Ideal	0	1	1893.6	1204.4
2	GWO	74.83	0.405	1829.9	802.7
	PSO	186.22	0.373	1548.8	679.5
	SA	140.46	0.385	1651.4	724.5
	WOA	97.78	0.397	1757.4	771.0
	INC	146.32	0.400	1793.3	785.0
	P&O	111.18	0.393	1936.2	755.0
	Ideal	0	1	1915.6	834.8
3	GWO	23.60	0.254	1661.3	8876.8

	PSO	111.23	0.234	1406.2	7513.3
	SA	74.21	0.241	1499.4	8011.3
	WOA	38.71	0.249	1559.6	8525.3
	INC	36.97	0.207	1614.6	8588.7
	P&O	45.00	0.247	1563.2	8352.1
	Ideal	0	1	1705.5	8847.3
4	GWO	25.91	0.238	1553.5	8178.5
	PSO	110.82	0.219	1314.9	6922.3
	SA	77.18	0.226	1402.1	7381.1
	WOA	44.10	0.233	1492.0	7854.6
	INC	38.57	0.192	1525.6	7954.1
	P&O	54.98	0.231	1645.7	7694.7
	Ideal	0	1	1626.4	8231.8

According to Table 5, there is a clear trend towards a decrease regarding the solar PV system efficiency from scenario 1 to scenario 4. For scenario 1 there is an average efficiency, among all MPPT algorithms, of 0.642; for scenario 2 of 0.392; for scenario 3 of 0.239, and for scenario 4 of only 0.223. This reduction in average efficiency is due to the fact that in scenario 1 practically ideal test conditions are considered, i.e., a staggered irradiation profile and constant temperature and load, while in scenario 4 all the test conditions considered vary, from the irradiation curve, the ambient temperature, to the load, which corresponds to real measurements. Variations in solar irradiation and temperature directly affect the energy produced by PV panels, while the variation in load also creates an extra disturbance in the MPPT controller.

In all the scenarios evaluated, the GWO-optimized MPPT algorithm has a lower RMSE compared to the other MPPT algorithms, with the lowest RMSE obtained for scenario 3 by the GWO with a value of 23.6, and the worst case for scenario 1 by the PSO algorithm with a RMSE value of 207.92.

According to the results, on the maximum powers reached by the MPPT, the PSO algorithm has the maximum and minimum values in output power. The maximum output power value is 1936.2 W, for scenario 2 using the PSO; while the minimum output value is 1314.9 W, for scenario 4. These maximum and minimum values are because the PSO algorithm causes high positive and negative peak values, having an output with large oscillations for these two scenarios.

Regarding the performance indicators shown in Table 9, the most representative of all is the total energy generated (Wh), since it indicates which controller manages to extract the most power from the solar PV array in the test time for each scenario. In all scenarios, the algorithm that manages to extract the most power in the test time is the GWO. The maximum value of energy generated is in scenario 3, where the GWO manages to extract 8.8768 kWh, even surpassing the estimation made by the ideal mathematical model of the solar PV array.

For scenario 1, the algorithm that manages to generate the greatest amount of energy from the solar PV array is the GWO with 1.2091 kWh, followed by the INC with 1.1650 kWh; for scenario 2 the best is again the GWO with 0.8027 kWh followed by the INC with 0.7850 kWh; for scenario 3 the GWO is the best with 8.8768 kWh followed by the INC with 8.5887 kWh; and finally, for scenario 4 the best is the GWO with 8.1785 kWh followed by the INC with 7.9541 kWh. Previous results are consistent that the INC algorithm is generally better than the P&O for variable irradiation conditions. However, the GWO-optimized controller is shown to perform better compared to the INC MPPT algorithm.

Before carrying out tests with operating scenarios under variable conditions, it was proceeded to evaluate the behavior of the PV array for controlled changes of solar irradiation, to analyze the settlement times in the search for the maximum power point for each irradiation step as well as the behavior of the current and voltage and its related power for each proposed algorithm. Figure 13 shows the power, current, and voltage curves for different levels of constant irradiation.

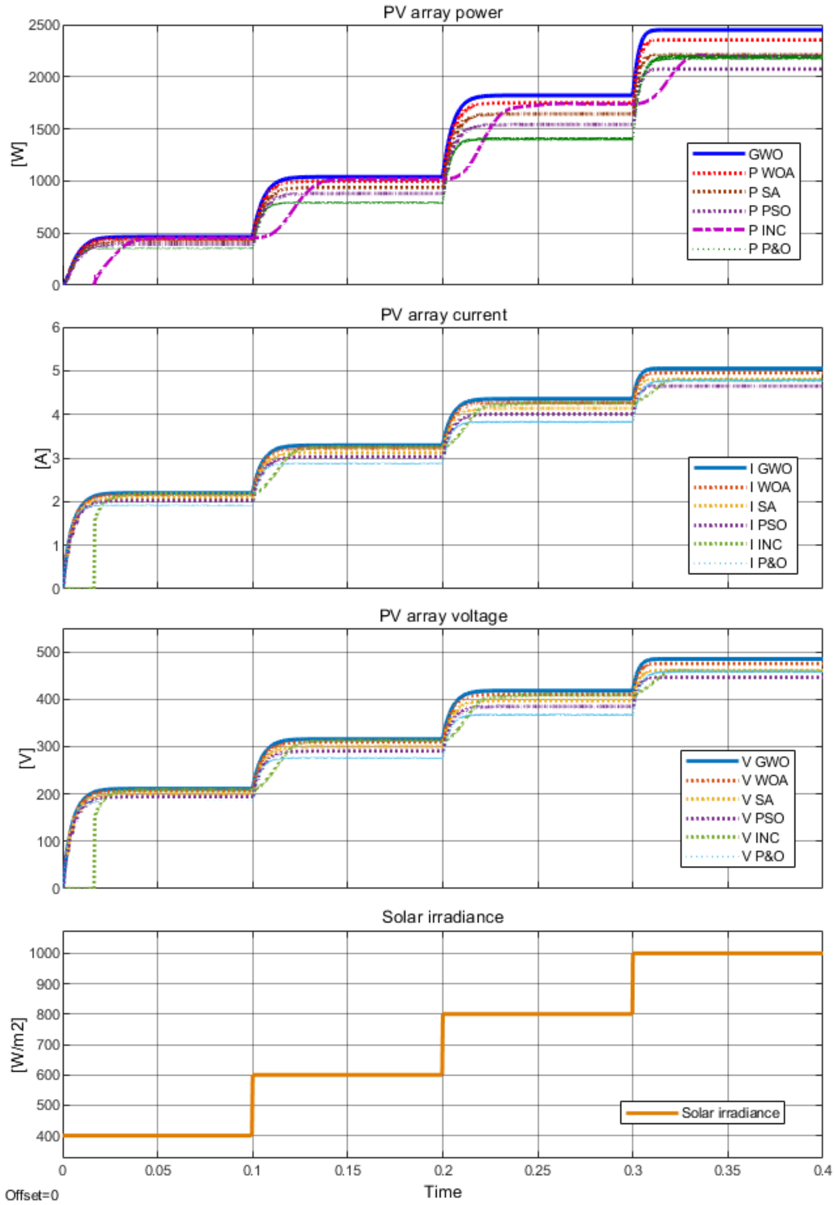


Figure 13. Comparative plot of power, current and voltage for the PV array operating at different levels of constant irradiation, for each algorithm evaluated.

As can be seen in Figure 13 above, of the algorithms evaluated and for each level of solar irradiation, the controller the proposed GWO MPPT controller has the highest levels of current and voltage, and therefore, power, with a short response time compared to other algorithms. It is noted that INC MPPT controller has the slowest response to changes, while P&O has response times similar to GWO less at the start which takes longer to find the right duty cycle than the other algorithms, however, both achieve lower power levels than GWO.

In applications of search for maximum points of power, the speed with an algorithm finds that point is important. The speed with which it reaches maximum power helps the system cope effectively with sudden changes and disturbances in environmental conditions. Table 6 shows the settling times (Ts) concentration for each algorithm and different solar irradiation levels. Lowest Ts are colored in bold green color, and higher Ts are colored in bold red color.

Table 6. Settlement time for irradiation steps comparison.

	Solar irradiation change (W/m^2)							**Algorithm average Ts (s)**
	0-400	400-600	600-800	800-1000	1000-800	800-600	600-400	
	Settling time, Ts (s)							
GWO	0.0250	0.0200	0.0200	0.0070	0.0150	0.0160	0.0190	0.0175
WOA	0.0400	0.0300	0.0320	0.0180	0.0300	0.0180	0.0250	0.0280
SA	0.0400	0.0350	0.0330	0.0120	0.0280	0.0200	0.0210	0.0270
PSO	0.0350	0.0340	0.0310	0.0150	0.0270	0.0220	0.0220	0.0270
INC	0.0500	0.0500	0.0440	0.0310	0.0400	0.0360	0.0400	0.0420
P&O	0.0200	0.0200	0.0200	0.0100	0.0160	0.0210	0.0170	0.0178
Average irrad. Ts	0.0350	0.0315	0.0300	0.0155	0.0260	0.0222	0.0240	

The settling time (Ts) of a controller is considered to be when the system's response reaches 0.98 of its maximum value with respect to its reference. It is remarkable how the Ts is different for changes from less to more than from more to less solar irradiation. Lower Ts rates are found for higher irradiation values. Of all the irradiation changes evaluated, the highest Ts was for the INC algorithm with a value 0.050 seconds for a solar irradiation step from 0 to 400 W/m^2, and the lowest Ts for the GWO proposed MPPT algorithm with 0.007 seconds for an irradiation step change from 800-1000 W/m^2.

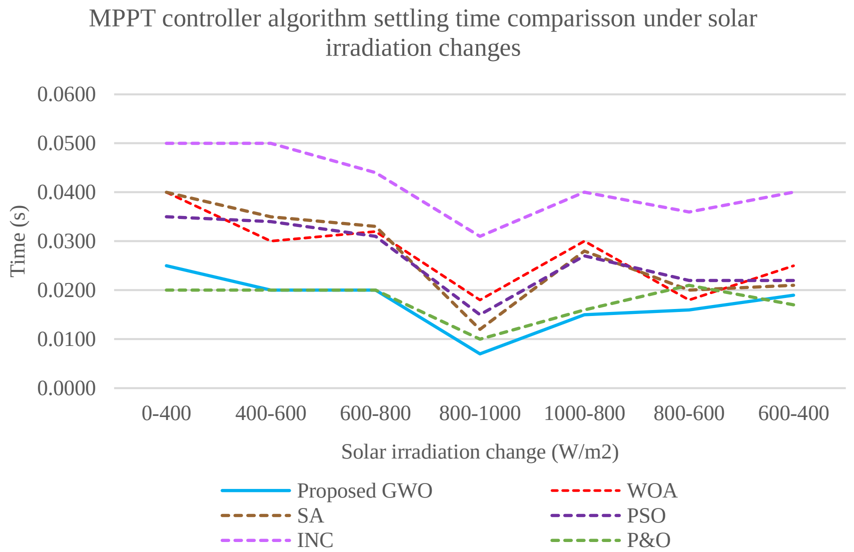


Figure 14. Comparison of MPPT controller algorithm settling time speed under solar irradiation changes.

As can be seen in Figure 14 above, the P&O algorithms and the one proposed optimized by GWO have similar response times for solar irradiation of between 400 to 800 W/m^2, however, for irradiation below 400 W/m^2 and above 800 W/m^2 the P&O takes on average 7% more seconds to respond compared to the GWO. The following four subsections show the simulated performance tests of MPPT controller algorithms under different operating scenarios. Table 7 summarizes a comparison of the results obtained from the different algorithms tested in relation to other works in the literature.

Table 7. MPPT algorithm perfomance comparison related to other works.

Algorithm	**Tracking time (s)**	**Iterations**	**Implementation complexity**	**Steady state oscillations**	**Ref. Work**
Proposed GWO	0.018	<3	Moderate	No	This work
WOA	0.028	<3	Moderate	No	
SA	0.027	<3	Moderate	No	
PSO	0.027	4	High	Yes	
INC	0.042	n.a.	Low	Yes	
P&O	0.018	n.a.	Low	Yes	
GWO	1.490	n.a.	Moderate	No	(S. Mohanty et al., 2016)
MBOA	0.720	n.a.	Moderate	No	(Shams et al., 2021b)
MVPA	0.530	n.a.	Moderate	No	(Pervez et al., 2021b)
ITGA	0.900	n.a.	High	No	(Shams et al., 2021d)
ISSA	0.200	<5	Moderate	No	(Fares et al., 2021b)
SSA	0.480	<5	Moderate	Yes	
PSO	0.400	n.a.	High	Yes	
GA	0.253	n.a.	High	Yes	
ABC	5.320	10.2	Moderate	Yes	(Benyoucef et al., 2015)
OD-PSO	1.860	8	High	No	(Li et al., 2019)
ACO-PO	3.150	3.5	High	No	(Sundareswaran et al., 2016)

As can be seen in Table 7 above, the speed of settlement, or tracking of the maximum power point, varies from one author to another. This traking time depends in part on the design of the power converter associated with the MPPT controller of each job as well as the adjustment parameters each optimization algorithm. The number of iterations is an important parameter to consider, because it indicates the complexity of calculation that each MPPT must perform to reach the maximum power point, a smaller number of iterations will mean a hardware implementation with lower computing power requirements. The level of implementation complexity is related to the number of tuning parameters that each algorithm requires prior to its use. Steady-state oscillations refer to the system's response once the maximum power point has been reached, a response without oscillations is desirable since the system will be subject to less stress and therefore less stress and other peripheral effects related to power electronics and electrical signals.

Scenario 1: Constant load and temperature with staggered irradiation

To evaluate the response of the MPPT controllers for this case allows to know its performance under well-controlled environmental conditions: with a constant load and a constant environmental temperature of 25 °C, with a staggering irradiation curve shown in Figure 15.

The main objective of this scenario is to evaluate the performance of the different MPPT algorithms under stable operating conditions. Figure 15(a) shows the power curves obtained; it is observed that the GWO optimized MPPT has the closest curve to the ideal model. Figure 15(b) shows the different efficiencies, it is observed that the average efficiency varies according to the level of solar irradiation to which the PV solar array is subjected, obtaining the best efficiencies for values close to 800 W/m^2 constants. Figure 15(c) shows the input profiles for the models; for this scenario, the only parameter that must vary is the solar irradiation, and it is done in a staggered manner. Figure 15(d) shows the curves of accumulated power over the simulation time. Since, for this scenario, there is solar irradiation at all times, the slope is always positive.

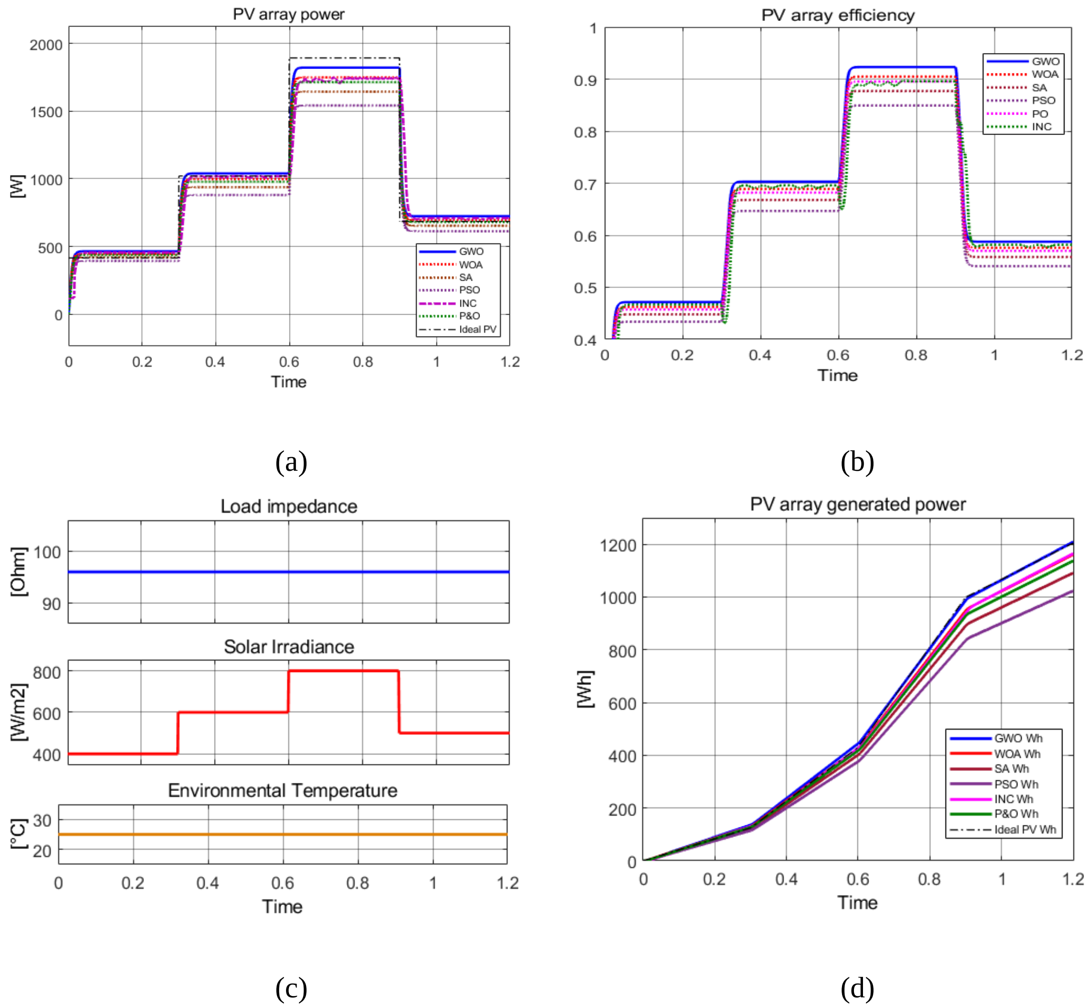


Figure 15. (a) PV array output power, (b) PV array efficiency, (c) Environmental conditions and load, and (d) PV array generated power.

Scenario 2: Variable load and temperature with staggered irradiation

Under this scenario, while solar irradiation is still staggered, the system is now subjected to variable load and ambient temperature conditions. This makes it possible to identify the system's response to typical fluctuations due to variable consumption and consider changes in the ambient temperature. Figure 16 shows graphs of the PV system responses under the conditions described for this scenario.

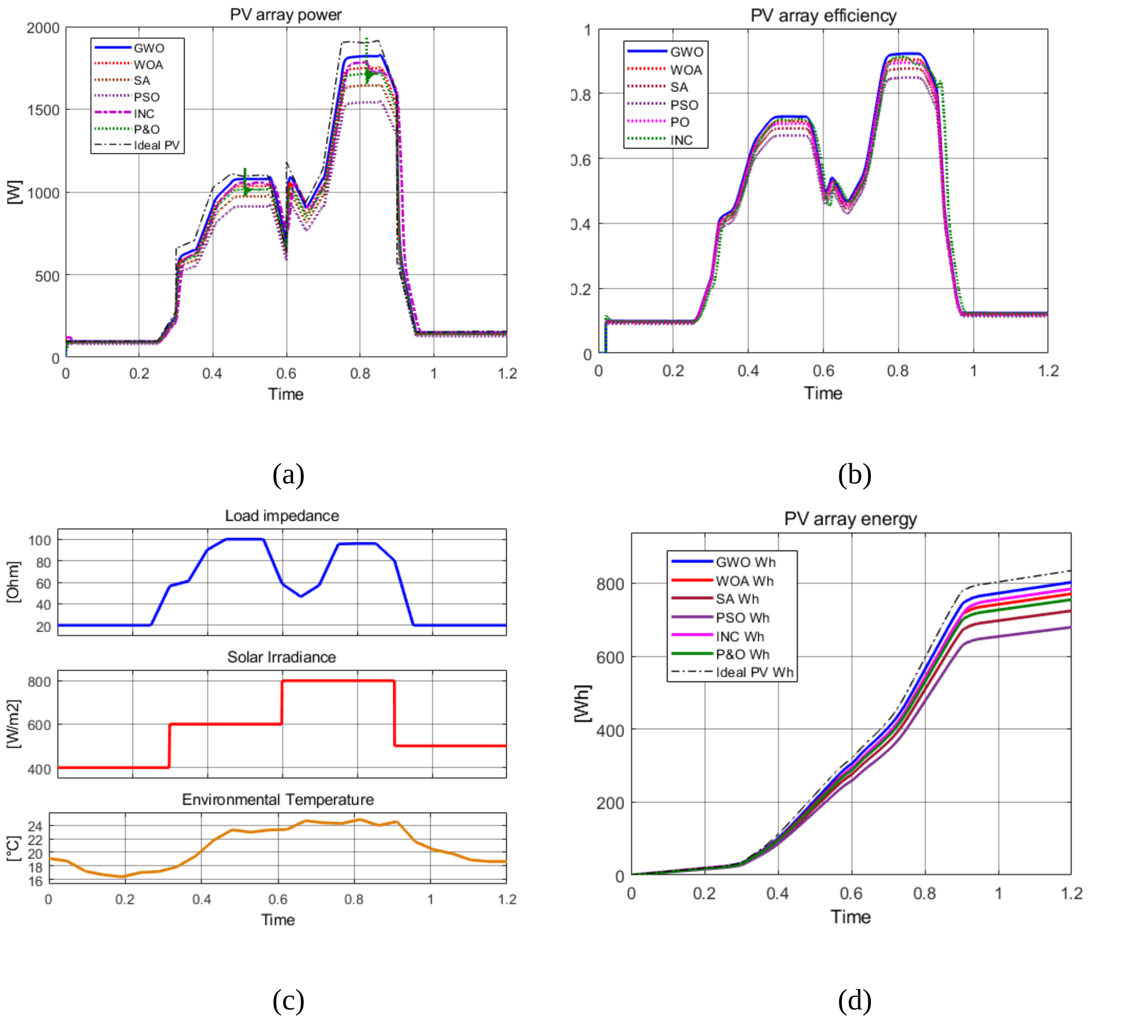


Figure 16. (a) PV array output power, (b) PV array efficiency, (c) Environmental conditions and load, and (d) PV array generated power.

As can be seen in Figure 16 above, the output power curve, see Figure 16(a), is deformed with respect to the previous case, despite being subjected to the same influence of solar irradiation, this is because the system is now subjected to a variable load on the MPPT power converter output. This evaluates the ability of the different controllers to provide energy to a system whose electricity consumption changes over time and considers changes in ambient temperature. Figure 16(b) shows how efficiencies are reduced compared to the previous case; although the accumulated generated power curve has a positive slope (Figure 16(d)), which is smaller.

Scenario 3: Constant load and temperature with variable irradiation

In the third evaluation scenario of the different MPPT controllers, constant temperature and load conditions are considered, but unlike the previous scenarios, a real irradiation profile is now used over a day. Figure 17 shows the system's response to these conditions.

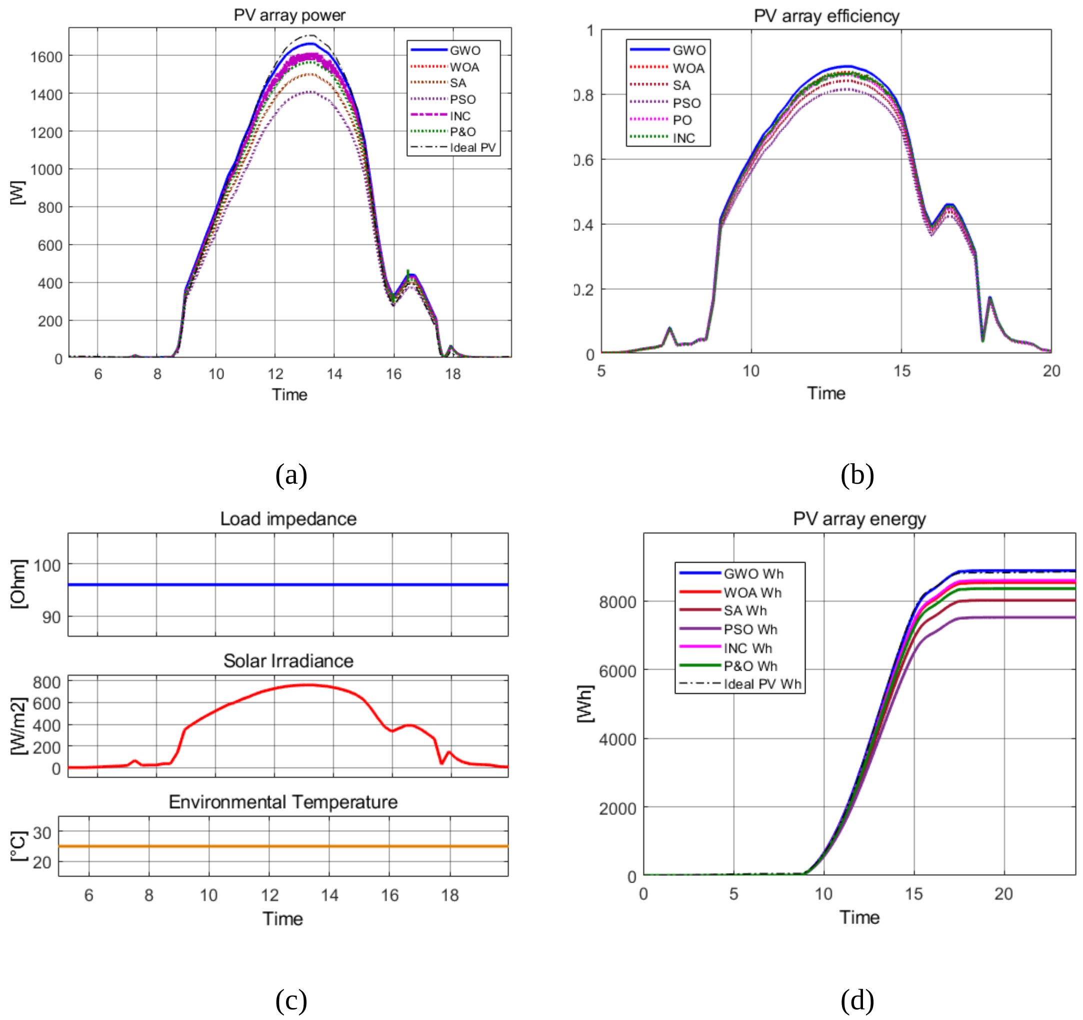


Figure 17. (a) PV array output power, (b) PV array efficiency, (c) Environmental conditions and load, and (d) PV array generated power.

This scenario is the plumber that contemplates a real irradiation curve measured over 24 hours. The performance of the controllers was validated under conditions of variable irradiation but constant load and temperature. Interesting changes can be seen with respect to the two previous scenarios, which are typically used for performance tests. Figure 17(a) shows how solar irradiation affects the solar panels' output power. The efficiency range, see Figure 17(b) above, of 0.8 is reduced only at peak solar hours. The power curve accumulated over time exhibits slopes equal to zero before 10 hours and after approximately 17 hours, see Figure 17(d), this is because the irradiation levels are insufficient to generate more energy beyond what was previously achieved.

Scenario 4: Variable load and temperature with variable irradiation

Finally, the operation of the MPPT controllers was evaluated according to their performance, using only variable data as inputs, achieving a representation closer to reality for this comparison. This fourth scenario considers as much load as variable temperature and irradiation. Figure 18 shows the system response for each proposed algorithm. This is the last scenario evaluated, here in addition to having considered variable irradiation, variable energy demand and temperature curve are also considered, being the scenario closest to reality. In Figure 18 (a), the output power curves now depend not only on solar irradiation but also on energy demand and are affected by changes in the ambient temperature. The average efficiency in this scenario, see Figure 18(b), barely exceeds 0.8. In this case, as in the previous scenario, it is observed that in Figure 18(d) there are regions in which the curves of accumulated power over time have slopes equal to zero, this is due to the insufficiency of solar irradiation to generate significant power during those time intervals.

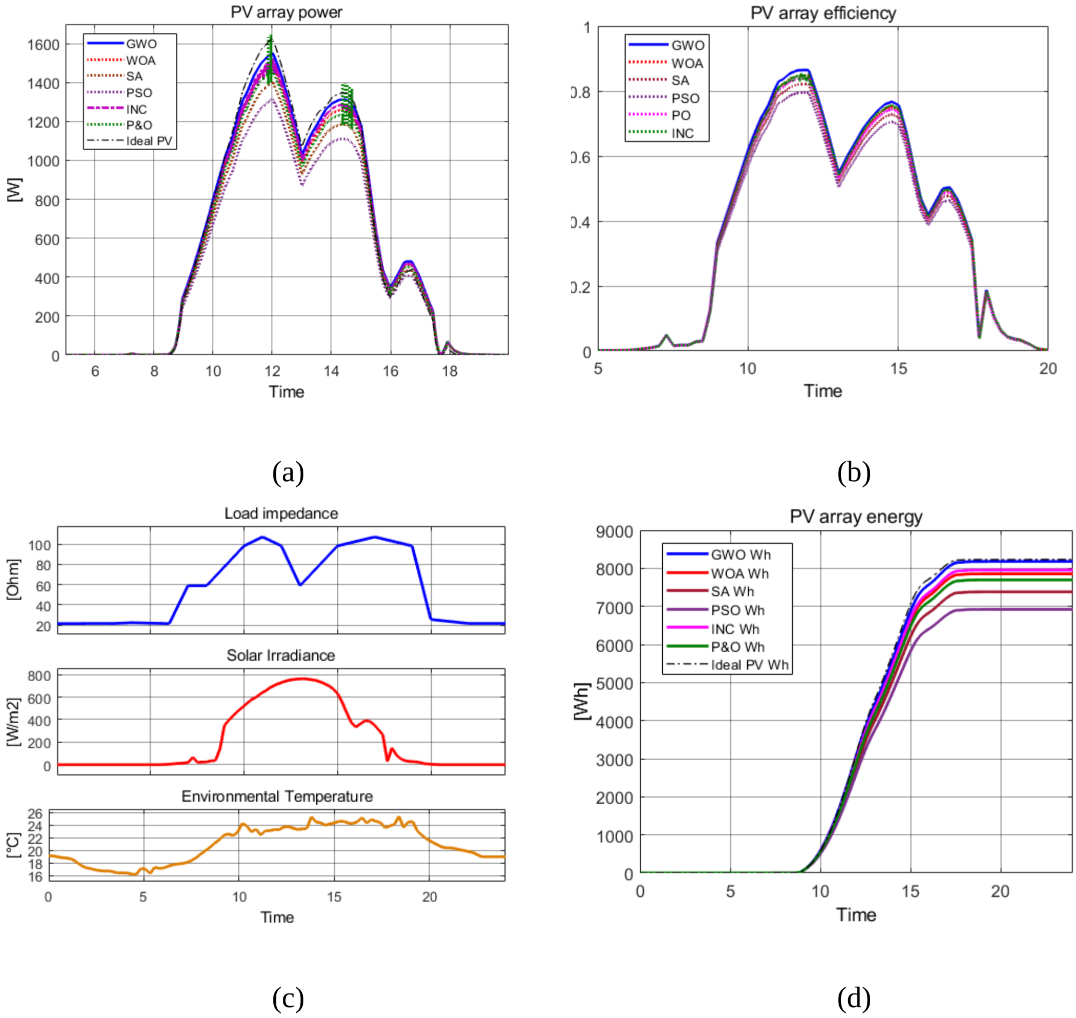


Figure 18. (a) PV array output power, (b) PV array efficiency, (c) Environmental conditions and load, and (d) PV array generated power.

Conclusions

In this work, a MPPT controller optimized by metaheuristic algorithms is presented. The performance of the proposed controller was compared using four different optimization algorithms, GWO, PSO, SA, and WOA, against the commonly used algorithms P&O and INC. The algorithms were evaluated under four different scenarios under constant and variable irradiation, load, and temperature conditions. The comparative study determines which of the MPPT controller algorithms performed best. In all cases, the MPPT controller optimized by GWO has better performance rates, with a lower RMSE between the output power obtained and the output power of the reference. The GWO had an efficiency higher than 3% of the average in scenarios 1 and 2 with staggered solar irradiation. In scenarios 3 and 4 with variable irradiation, its efficiency was 6% better than the average efficiency of all MPPT algorithms compared.

Similarly, it was obtained that the net power generated is higher by the MPPT controller optimized by GWO, on average 3%, than the average for all scenarios. The GWO-optimized MPPT algorithm extracted 8,178 Wh, while the INC and P&O-based algorithm extracted 7,954 and 7,694 Wh respectively, obtaining the GWO 3% and 6% more power compared to inc and P&O. As for maximum instantaneous power values, the PSO had larger values due to short energy peaks since the controller responded with important impulses in the changes. In addition to the analysis on efficiency and total power obtained for each algorithm, a comparative analysis was also carried out on the response time to irradiation changes for each of them. It was observed that the slowest algorithm was the INC with an average response time to changes of 0.042 seconds, while the fastest was the GWO with an average time of 0.0175 seconds, followed by the P&O in second place, 7% slower on average for the scenarios evaluated.

According to the comparison of the MPPT algorithms for controller's performance (traditional and P&O and INC as bio-inspired such as GWO, PSO, SA, and WOA), it can be concluded that the GWO optimization algorithm was shown to be efficient for control applications since its performance was between 3% and 6% better and without over impulses. Also, it can be said that, through the proposed methodology, it is possible to validate different MPPTs under variable conditions of irradiation, temperature, and load; being the MPPT controller optimized by the GWO algorithm the most effective of all the algorithms.

As for the limitations of the use of metaheuristic techniques for their application in MPPT controllers, when these algorithms are implemented in a programmable logic controller the MPPT algorithm must be tuned, feeding it with previous irradiation data under different weather scenarios, with the aim that the controller finds its optimal configuration for the search for the maximum power point, unlike using traditional techniques, such as P&O or the ICO, where the controller does not require a previous setting for its operation. However, bio-inspired algorithms applied to MPPT controllers have the advantage that they allow finding solutions that classical or mathematical methods cannot locate in the universe of tuning possibilities of a given controller.

Future work remains the exploration of optimization not only of the MPPT controller but also of the construction of the associated power converter itself and a more detailed study of the system's response to a greater number of disturbances and a physical implementation for further validation.

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List of Acronyms

ABC	Artificial Bee Colony
ANN	Artificial Neural Network
CS	Cuckoo Search
DC	Direct Current
DFO	Dragonfly Optimization
FA	Firefly Algorithm
FI-GMPPT	Fast and Intelligent Global Maximum Peak
FL	Fuzzy Logic
FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
GMP	Global Maximum Peak
GWO	Grey Wolf Optimizer
GWO DPID-MPPT	Grey Wolf Optimizer Discrete-time PID Maximum Power Point Tracker
INC	Incremental Conductance
kW	Kilowatt
MFA	Modified Firefly Algorithm
MO	Multiverse Optimizer
MOSFET	Metal–Oxide–Silicon Field–Effect–Transistor
MPO	Modified Perturb and Observe
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
OA	Optimization Algorithm

OATCA	Optimized Ten Check Algorithm
P&O	Perturb and Observe
PID	Proportional-Integral-Derivative
PSO	Particle Swarm Optimization
PV	Photovoltaic
PWM	Pulse–Width Modulation
LMDS	Large and Mutable Duty Step
LSDS	Large and Small Duty Step
RES	Renewable Energy Sources
RMSE	Root Mean Squared Error
SA	Simulated Annealing
SOS	Symbiotic Algorithm Search
SSA	Salp Swarm Algorithm
TCA	Ten Check Algorithm
W	Watt
Wh	Watt-hour
WOA	Whale Optimization Algorithm

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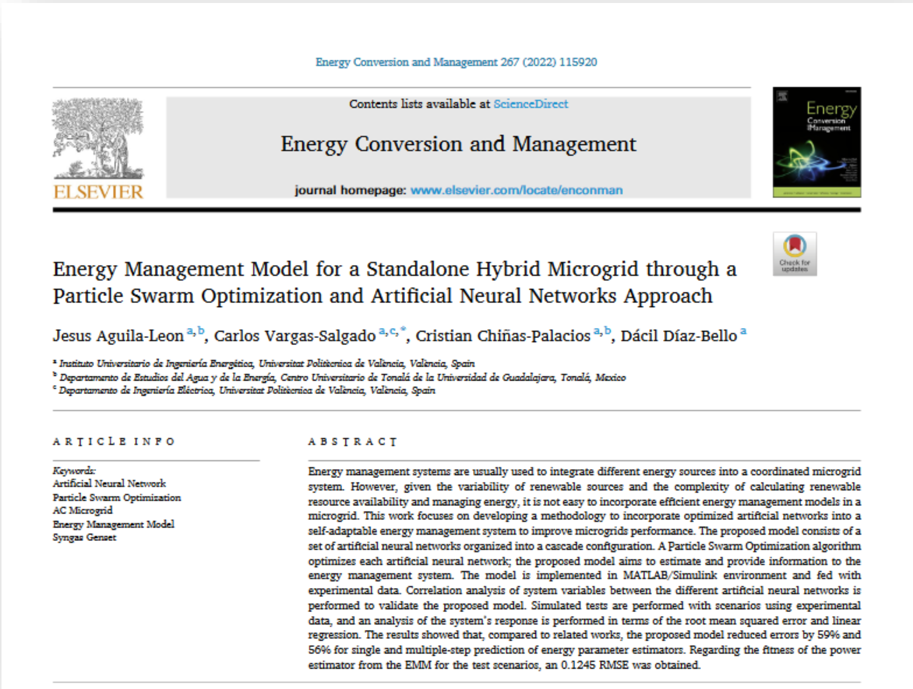
2.3 Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach



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Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach

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ABSTRACT

Energy management systems are usually used to integrate different energy sources into a coordinated microgrid system. However, given the variability of renewable sources and the complexity of calculating renewable resource availability and managing energy, it is not easy to incorporate efficient energy management models in a microgrid. This work focuses on developing a methodology to incorporate optimized artificial networks into a self-adaptable energy management system to improve microgrids performance. The proposed model consists of a set of artificial neural networks organized into a cascade configuration. A Particle Swarm Optimization algorithm optimizes each artificial neural network; the proposed model aims to estimate and provide information to the energy management system. The model is implemented in MATLAB/Simulink environment and fed with experimental data. Correlation analysis of system variables between the different artificial neural networks is performed to validate the proposed model. Simulated tests are performed with scenarios using experimental data, and an analysis of the system's response is performed in terms of the root mean squared error and linear regression. The results showed that, compared to related works, the proposed model reduced errors by 59% and 56% for single and multiple-step prediction of energy parameter estimators. Regarding the fitness of the power estimator from the EMM for the test scenarios, an 0.1245 RMSE was obtained.

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Esta es una publicación sobre control secundario y terciario de una microrred. El sistema se compone de diversas fuentes generadoras: un banco de baterías, una planta de gasificación como respaldo y un arreglo solar fotovoltaico. El dimensionamiento de la microrred del modelo se hizo con base a los equipos existentes en la microrred experimental del Laboratorio de Energías Renovables (LabDER) de la Universitat Politècnica de València. Se propone y simula un modelo de gestión de la energía para la microrred integrando tanto algoritmos de optimización bio-inspirados como redes neuronales artificiales en el mismo sistema. Esta integración permite predecir de manera óptima la energía requerida, y en el caso de la planta de gasificación la materia prima requerida, para producir energía según la demanda energética. Se validan diferentes tipos de redes neuronales contra el modelo propuesto basado en una red neuronal artificial optimizada mediante algoritmo de Particle Swarm Optimization (PSO). Los resultados y metodología se detallan a continuación.

Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach

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Keywords: Artificial Neural Network; Particle Swarm Optimization; AC Microgrid; Energy Management Model; Syngas Genset.

Abstract

The efficient integration of various technologies, in the form of microgrids (MG), for the use of renewable energy sources (RES) is an important challenge considering the natural variability of both the availability of renewable resources and the energy demand. An Energy Management Model (EMM) for hybrid renewable systems is essential to provide energy to loads efficiently and reliably improving the performance of the MG. For that purpose, an EMM for a standalone hybrid microgrid incorporating a Particle Swarm Optimization (PSO) algorithm and an Artificial Neural Network (ANN) approach is presented. This research focuses on the operation of the renewable sources available in a Microgrid (MG) aided by a centralized controller. The MG consists of a PV solar array, a syngas gasification plant, an energy storage system, and a programable load to adjust the energy demand. To model the microgrid, a set of ANNs in cascade configuration is used, then the PSO algorithm optimizes each ANN to improve its performance. The model was implemented using MATLAB/Simulink. The ANNs were trained with historical data of an experimental MG. To evaluate the performance of the proposed model, an analysis of the outputs of the set of ANNs used is carried out through a study of correlation of variables and linear regression. The results show that the proposed ANN-based EMM has a good fit compared to real measurements, and therefore, is a feasible model to estimate the energy outputs and the required resources to cover the energy demand in a MG.

Introduction

In recent years, due to the previous decades indiscriminate use of fossil fuels to obtain energy, the interest in the integration of generation technologies based on renewable energies in Hybrid Renewable Energy Systems (HRES) in the form of electric Microgrids (MGs) has taken more and more prominence [1–3]. However, the intermittent and unpredictable nature of renewable energy sources is a problem in ensuring the reliability of the renewable energy technologies [4]. To improve the performance, and therefore, the reliability of the MGs, various strategies can be implemented, from the optimization in their design and sizing to the development and implementation of Energy Management Models (EMM) and Energy Management Systems (EMS) [5,6]. In addition to the variability of the renewable energy sources availability, energy demand is also difficult to predict since it depends on the preferences of each user and their behavior, which increases the instability of the MG [7].

Efficiently managing the resources of the MG is a task of the EMS [8]. The EMSs can be classified into two main categories: centralized and decentralized [9]. Centralized EMS are based on a central controller within the microgrid, which, according to the information it receives and operating rules or algorithms, can make decisions to manage energy flows in the microgrid [10]; meanwhile decentralized EMS are incorporated into decentralized control topologies, where droop control plays an important role in managing the various energy sources and energy storage systems to establishing energy flows policies into the microgrid [11].

Conventional EMS algorithms are based only on the energy balance of the MG, these methods are usually inefficient since they do not consider other inherent aspects of the complexity and nonlinearity of microgrids [12], such as estimations of the availability of resources, learning historical data of user energy demand, climate variability in the region as well as detailed characteristics of energy storage and backup systems, such as the SoC in battery banks or suitable parameters for configuration and operation of the MG subsystems.

Creating an exact mathematical model of the microgrid and its components that allows its integration into an EMS is a very complicated task given the large number of variables involved. An alternative to obtain a model of the microgrid subsystems that allows its adaptation to an EMS is using metaheuristic algorithms [13]. Nature is a source of inspiration for developing various modern metaheuristic algorithms, those algorithms mimic nature systems and phenomena, and translate them into computational methods [14]. Metaheuristic algorithms are a powerful tool, which in the field of MG its application can be classified into the following categories: optimal design of components and systems [15], optimal sizing [16], optimal control [17], prediction of resource availability and energy management [18–20].

Artificial neural network (ANN) algorithms are currently an interesting alternative for predictive modeling and control due to their robustness and handling capacity for complex non-linear relationships in dynamic systems, for example, Smart Grids [21,22]. Those algorithms are based on biological neural network learning rules and procedures.

Several authors have performed improvements of MG systems using artificial neural network (ANN) algorithms, in [23] a hybrid model of an ANN with Particle Swarm Optimization (PSO) allowed the estimation of the power generated by a Biomass Gasification Plant (BGP) in order to effectively cover the energy demand in an experimental MG. A dynamic voltage restorer (DVR) is applied in [24] by determining an ANN to protect sensitive loads from voltage disturbances. Furthermore, [25] carried out two ANNs to adjust the power converters' pulses for the Voltage Source Inverter (VSI) used to control the DVR by regulating the voltage signals.

Another example of ANN applied in renewable energy generation is [26], which develops various ANN-based Maximum Power Point (MPP) tools to maximize the efficiency of photovoltaic panels, considering many electrical and environmental photovoltaic input parameters with six different scenarios to investigate their influence on the MPP prediction accuracy. A total of six combinations were applied by the authors, combining electrical and thermal (Voc, Isc, FF) and environmental (RH, atmospheric pressure, PV back surface temperature, and irradiance information) parameters, outputs were validated by the root mean squared error (RMSE). Authors in [27] conducted a study to assess the feasibility of ANNs and Nonlinear Autoregressive Exogenous (NARX) neural network models to model a fixed-bed downdraft gasification and to know the relation between the features of the gasifier and the regression performance. To achieve this, different feature groups were introduced: the first one consisted of the equivalence ratio (ER), airflow rate (AF), and temperature distribution; while the second one included biomasses value such as the equivalence ratio (ER), air flow rate (AF), and the reduction temperature. Thus, after comparing the NARX and ANN models, when using the temperature distribution as a feature, it is concluded that both methods are reliable, accurate, fast, and effective to control and optimize a woody biomass gasification process and thus syngas composition and calorific value.

However, neural networks are not only used for modelling renewable systems, but also for assessing the results of other models, as in the case of [28], in which the results obtained from mathematical models are compared using R coefficient, Mean Square Error (MSE) and RMSE in order to design a photovoltaic/thermal (PV/T) system to reduce the temperature of the PV cell (using nano Phase Change Material (PCM) and a nanofluid cooling system. Regarding the question of power exchange between generation sources in a microgrid, bio-inspired algorithms have had a great performance related to the improvement of the optimal energy production. In [29] it was shown that an adequate energy management system incorporating a Fuzzy Inference

System (FIS) with a genetic algorithm (GA) helps maximize the benefit of energy exchange in the network. In addition, in [30] the same problem was addressed in a multi-microgrid environment by combining a Stackelberg game of game theory with a quasi-oppositional symbiotic organism search algorithm to improve energy exchange trough a centralized MG controller incorporating a parallel fuzzy logic inference engine.

Other authors use different ANN tools for energy management in microgrids, an example is [31], which uses game theory, specifically canonical coalition games to model an Energy Management System (EMS) able to optimize the power exchange management in networked microgrids connected to the grid. Besides, not only one EMS, but a network of local EMS and a central EMS is proposed. Its main aim is to develop a power exchange strategy able to minimize transmission and transformation power losses with computational efficiency. To do so, a scheduled model is given to the canonical coalition game to generate a cooperative schedule for a changing horizon. The schedule generated is defined by each local EMS (of each microgrid), giving orders of the surplus or deficit power in each time. Authors in [32] developed a microgrid central controller using embedded energy management algorithms for decision making at an isolated renewable energy system with the assistance of multi-agent concept and multiple sensors at power sources, where sources like wind, solar, biogas and batteries are considered. Besides, a connection to the utility grid in case of lack of energy from the microgrid and a power control mechanism for the operation of batteries is considered (with constraints such as: not to charge batteries above 80% of their State of Charge (SoC), and not discharge batteries below 20 % of their SoC). Furthermore, in [33] for instance, models and designs the microgrid central controller upon the following rules applied to the energy management algorithm with the next priority sequence: first solar and wind sources, second biogas, then batteries and lastly connection to the utility grid. The use of ANNs is also useful not only to analyze the performance of power exchange between generation sources in microgrids, but also in terms of economics and emissions [34] compares the operation of a ground source heat pump and a photovoltaic thermal system for a single house for heating and cooling purposes according to the time of the year from an ANN based approach and a conventional on-off control.

Several authors have addressed the design of EMS with different approaches, with the aim of improving the performance of MG. Authors in [35] present a novel load management system for smart homes using neural networks and fuzzy logic for load classification, which achieves better scheduling of loads and an intelligent reduction in energy consumption, also adding layers of security to the system through metaheuristic techniques of cryptography for information. In [36] the authors used an EMS based on stochastic methods in optimization, where the proposed model can reduce operating costs by defining a day-ahead operation and maximizing the use of renewable resources. As mentioned before, ANN are a powerful tool for forecasting, in [37] an EMMS is presented that makes use of a trained ANN with historical data on generation power, consumption and SoC of the microgrid, with the aim of determining the optimal mode of operation of the microgrid; while authors in [38] compare a proposed ANN-based backtracking search algorithm (ANN-BBSA) versus an ANN-based binary particle swarm optimization (ANN-BPSO) with the aim of limiting fuel consumption, reduce CO2 emissions and increase efficiency in a MG. Authors in [39,40] pay special attention into forecasting parameters, uncertainty and demand response to increase MG reliability.

To the knowledge of the authors of this work, and according to the literature consulted, the integration of metaheuristic algorithms to EMS follows various methodologies from author to author. The performance of metaheuristic algorithms, whether ANN or optimization algorithms, is strongly related to both the adjustment of the parameters of these algorithms and the data with which they are fed. This paper presents the development of an energy management model (EMM), which integrates the use of ANN and optimization algorithms in order to improve its performance. The objective of the proposed model is to estimate in the best possible way the power outputs, and the main operating parameters of a microgrid, to cover an energy demand. The main contributions of this work are:

1. A new energy management model for a microgrid, incorporating a cascade configuration of ANN optimized by means of PSO algorithm.
2. A methodology for the analysis of ANN outputs applied to MG, using correlation and linear regression matrices.
3. Obtaining an EMM capable of estimating the operating parameters of the ESS and a syngas-based generation backup unit to optimally cover the energy demand in the MG.

Methodology

The methodology followed to develop the EMM proposed is detailed in this section. First, the general architecture of the off-grid microgrid system is described considering the power sources, storage system, other devices, and general characteristics. Then, the proposed EMM explains how the neural network is integrated into the energy management system. Finally, the simulation conditions used for the model are detailed.

Microgrid architecture

The standalone microgrid consists of a PV array as the primary renewable source. When power generated for the PV array exceeds the load energy demand, then energy is stored into a storage system. Additionally, a Biomass Gasification Plant (BGP) that feeds a Genset is available a backup system. The microgrid architecture considered for the developed EMM is depicted in Figure 1.

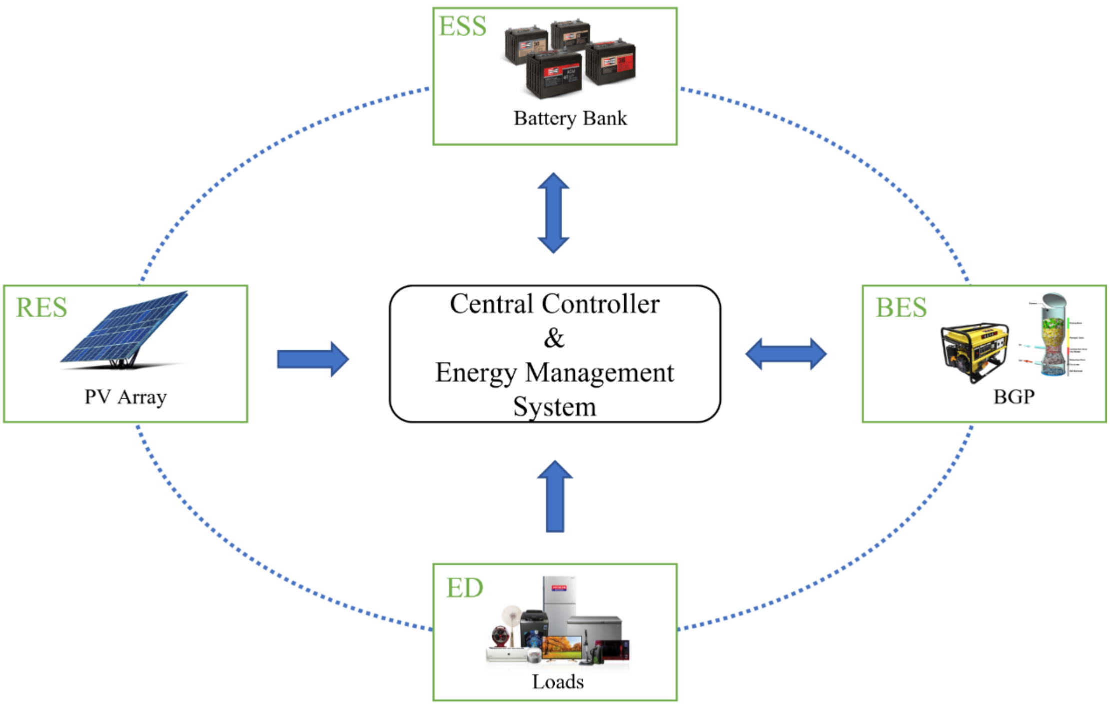


Figure 1. Overall architecture of the stan-alone microgrid for the proposed EMM.

As shown in the previous Figure 1, the operation of the MG depends on a centralized controller. The proposed EMM objective is to use the energy efficiently, making preferential use of the cheapest sources, such as the PV system, followed by the storage, and finally using the BGP to cover the user's energy demand. The main features of the microgrid are shown in Table 1.

Table 1. Microgrid main features for the proposed EMM.

Description	Main features
Photovoltaic array	2.1 kW, 12 solar panels
Syngas production and power generation	10 kW @ 28 Nm^3/h of Syngas and a 13 kg/h biomass consumption.
Storage system	Four Batteries in total 12 kWh storage capacity, 12 V @ 250 Ah batteries

*Adapted from [41]

The central controller receives information from the microgrid's sources and energy storage systems through sensors and Power Meters (PM) distributed in the microgrid.

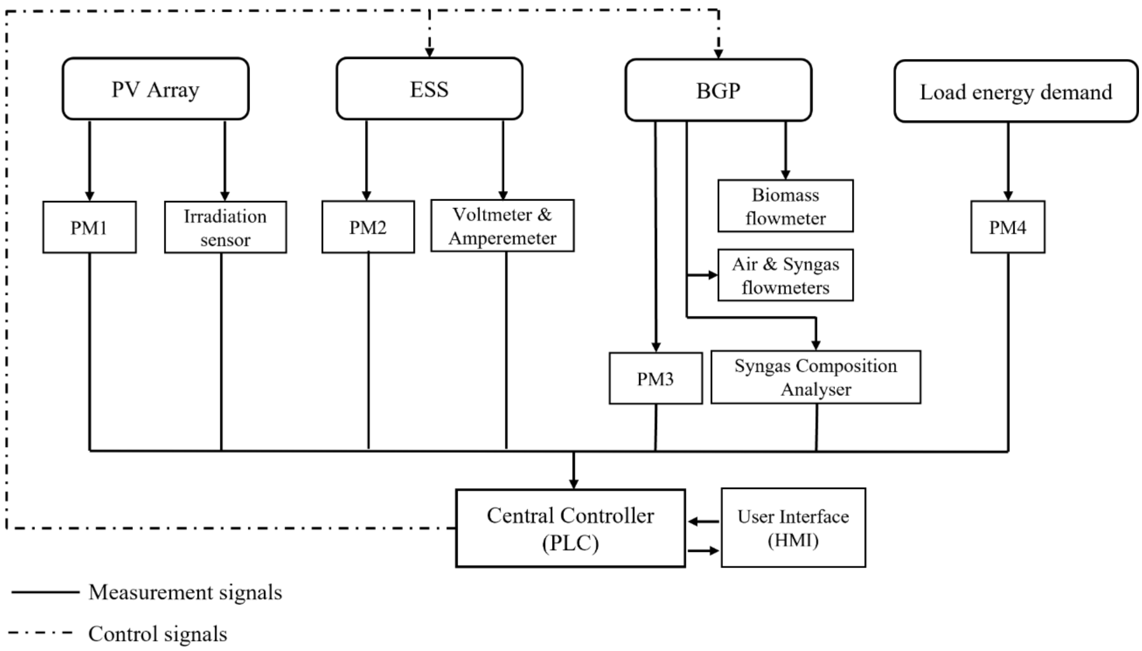


Figure 2. Control and measurement signals in the microgrid.

Since the primary goal of the EMM proposed in this research is to improve the energy management of the microgrid, collecting measurements of the electrical and environmental parameters is essential to make good decisions. Several sensors and PM are deployed along the microgrid for these purposes, as shown in Figure 2. The main components of the control system and measurement sensors are shown in Table 2 and Table 3, respectively.

Table 2. Control system components.

Description	Device
Four power meters	Siemens Sentron PAC3200
Programmable Logic Device (PLC)	Omron CJ2M-CPU11
Programmable Logic Device (PLC)	Omron CP1L
Communication module	Omron CJ1W-SCU31
HMI touchscreen	Omron NS5-SQ10B-V2

*Adapted from [41]

Table 3. Measurement sensor and devices deployed in the microgrid.

Parameter	Units	Sensor	Measurement range
Solar irradiance	W/m^2	CEBEK C0121	0-1100 W/m^2; ±40 W/m^2
Air velocity	m/s	EE65 Series HVAC	0-20 m/s; ±0.4 m/s
Syngas flow meter	m/s	CTV-100	0-30 m/s; ±0.4 m/s
Gas analyzer	%	GASBOARD-3100P	0-100%; 0.01 %

*Adapted from [41]

One PM measures the energy produced by the PV system according to the incidence of solar irradiation measured by the CEBEK C0121 sensor. In addition to measuring the power delivered and received during the discharge and charge process in the storage system, since the DoD must be estimated, it is also essential to collect voltage and current data. When the PV power generation is insufficient to meet the energy demand and the energy stored in the battery is not enough, the BGP covers the energy demand. In the BGP, the energy generated is measured through another PM. The biomass flow to be gasified is measured through the conveyor RPMs, and a gas analyzer measures the composition of the syngas produced and estimates the Lower Heating Value (LHV). Finally, the airflow and the syngas going into the Genset are measured by flow meters. The main features of the BGP and its related Genset are shown in Table 4 and Table 5, respectively.

Table 4. BGP main features.

Description	Feature
Gasification type	Bubbling fluidized bed
Biomass input @ 10%	5-13 kg
Biomass flow at power rating	10.5 kg/h
Efficiency	55-88%
Syngas production	10-28 Nm^3/h

*Adapted from [41]

Table 5. Genset main features.

Description	Feature
Brand	FG Wilson Generator
Model	UG14P1
Power rating	8.7 kW(syngas)
Velocity	1500 rpm
Compression ratio	8.5:1
Voltage and Frequency	230 V AC @ 50 Hz

*Adapted from [41]

The control and monitoring system integrated into the microgrid, and the EMM proposed are shown in Figure 3.

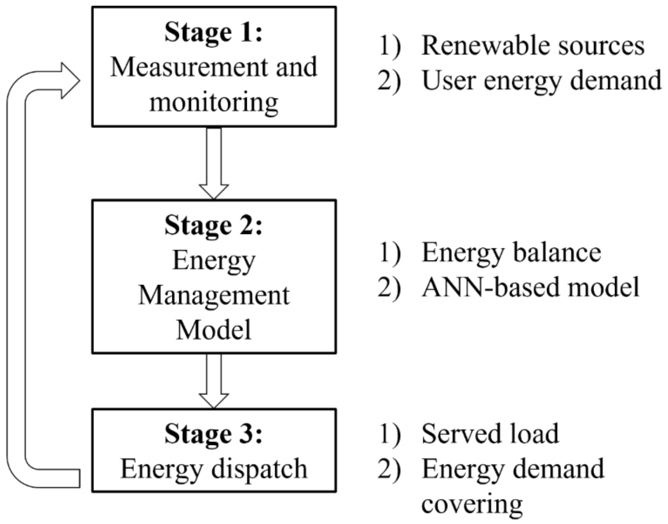


Figure 3 Workflow of the EMS in which ANN models are integrated.

The EMM proposed in this paper, as shown in Figure 3, integrates an ANN-based model for power backup. The model presented uses an ANN of the Cascade Forward Propagation (CF-P) optimized by the Particle Swarm Optimization (PSO) Algorithm. Figure 4 shows the inputs and outputs of the ANN used. The implemented model has a recurrent cascade-forward topology. The ANN model is divided into three subnets:

- The first subnet inputs are the solar irradiation, the year's season, and time; The output is the PV array power generation.
- The second subnet is fed during day-time-hours, and the PV array power generation is estimated, on the one hand, by the first subnet, and on the other hand by the storage system power, the power demand, the current unserved energy, the frequency, and power

factor as electrical parameters. The outputs of the second net are the energy demand to the BGP, the State of Charge (SoC) of the Energy Storage System (ESS), and the ESS power delivered

- In the third subnet, the inputs are the estimated energy demand to BGP, the SoC, and the ESS power delivered (estimated by the second subnet), the syngas composition, on the one hand. On the other hand, the frequency and the power factor are obtained as electrical parameters. The outputs are required biomass, syngas production, the airflow required in the Internal Combustion Engine (ICE), BGP power generated, and unserved energy, which is also an updated recurrent input to the previous subnet.

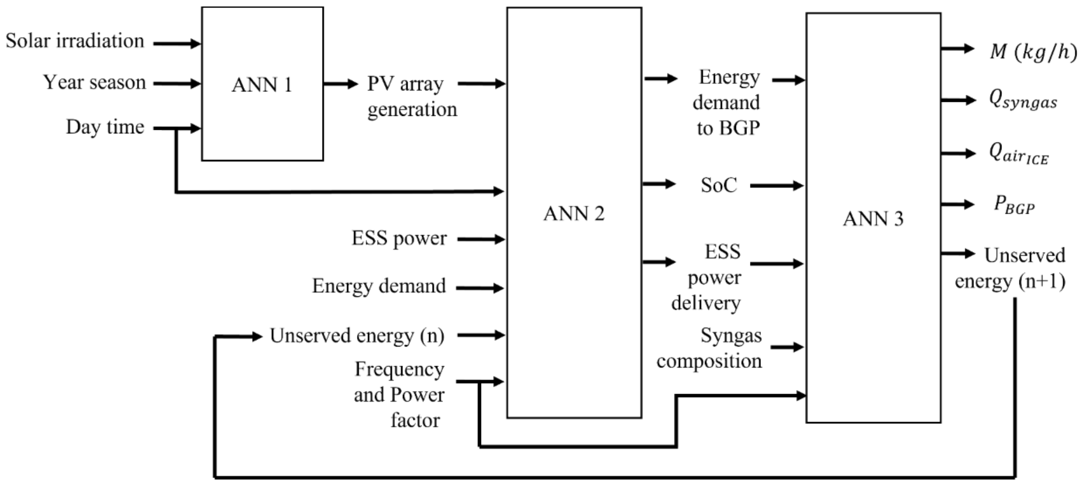


Figure 4. Artificial Neural estimation models inputs and outputs.

Before its use, the ANN is optimized by a PSO algorithm to find optimal values of weights and bias during the training. In this way, the error between the response of the real system and the predictions made by the model is reduced. The error between the actual response of the system and the response obtained by the prediction is measured in terms of the Mean-Squared Error (MSE). The PSO algorithm is based on the collective behavior of animal species for survival by emulating the foraging mechanisms of various animal species, being a generalization of those survival strategies [42]. In this work, as mentioned before, the PSO algorithm is integrated as an optimizer for the ANN employed in the EMM. The integration of the PSO algorithm and the ANN to the EMM is shown in detail in Figure 5.

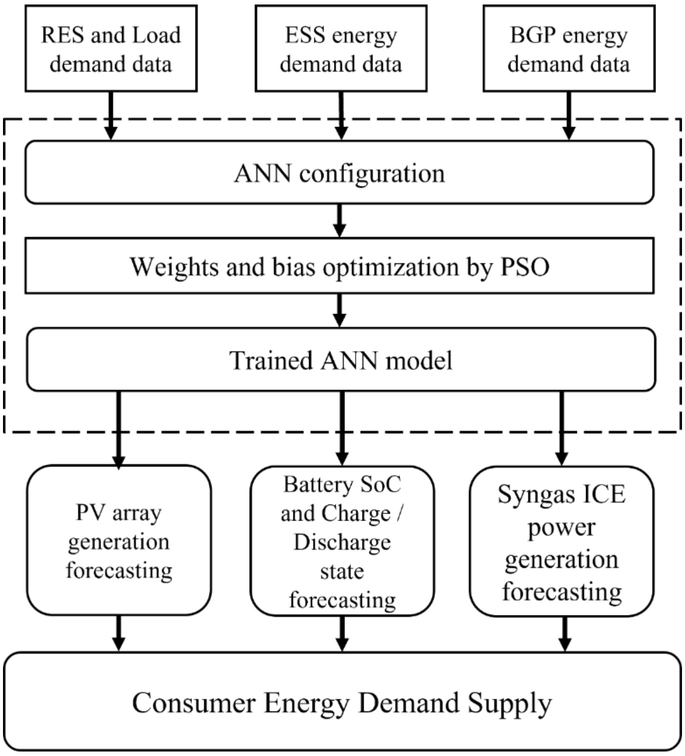


Figure 5. Integration of the ANN and the PSO algorithm to the proposed EMM.

Each entry signal to the ANN corresponds to a neuron of the input layer, as shown in Figure 5. Since the ANN simulates organic neurons' functioning, a training process is necessary. During the training process, a series of data are fed into the ANN to learn and subsequently be used to predict the system's output.

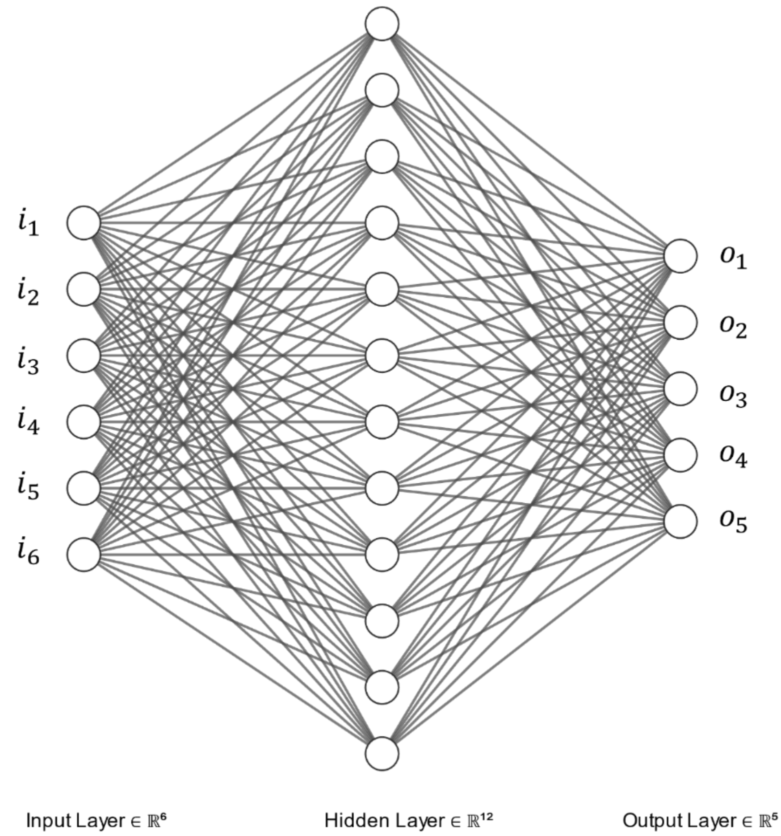


Figure 6. Overall structure of an ANN [43].

As shown in Figure 6, each neuron of the input layer is interconnected to the neurons of the hidden layer, and these in turn to the neurons of the output layer. The vector $I_{ANN} = [i_1, i_2, \ldots, i_n]$ represents the inputs (every data fed into the set of ANN). As in nature, the neurons of the ANN are connected by links, and as the process of training and learning takes place, the strength of those links increases. The strength of the interconnection link is called weight, and the weight of the link between a neuron a and a neuron b is defined by $w(a, b)$. The propagation function of the ANN is determined by equation (1) for each neuron of the input layer; the weighted sum transforms it in the activation functions (according to equation 2) for $n = 1$ to $n = 6$ in the next layer.

$$ANN_i = P_{fn_1}(o_{i_1}, o_{i_2}, \ldots, o_{i_n}, w_{i_1,j}, w_{i_2,j}, \ldots, w \qquad (1)$$

In equation (1) $o_{i_1}, o_{i_2}, \ldots, o_{i_n}$ are the output values of propagation function P_{fn_1}. In that sense, the activation function in the proposed ANN is defined by,

$$A_{fn_i}(t) = F_{act_i}(ANN_i(t), A_i(t-1), \phi_i) \quad (2)$$

Where the activation function is defined by F_{act_i} for each ANN used in the model, the n input in the network is A_{fn_i} and the activation status at the previous time is $A_i(t-1)$ for the i neuron. Once the ANN is ready, it is required to train it. The training aims to reduce the error between the output of the ANN and target values of evaluation. For this purpose, a proposed PSO algorithm has been integrated into the ANN to achieve better performance in ANN training by adjusting weights and bias during the training stage. Once the PSO algorithm is initialized, it randomly adjusts weights and biases in the ANN, and as the training iterations pass, these values are modified, according to specific previous parameters of the PSO, to reduce the MSE between the target values and the values predicted by the network. Each particle of the PSO algorithm corresponds to a different value of weights and bias in the ANN, which are adjusted in each iteration. These particles vary their position, velocity, and acceleration in the search space for possible optimal solutions. The optimal solution is considered to be one that meets the stop criteria requirements for the training algorithm and the PSO, either by the number of iterations and execution time or by the MSE error tolerance threshold. The vector W defines the optimization variables for the PSO algorithm according to equation (3) for k ANN, where *w* is the weight of each link between each pair of neurons i and j in the ANN. The number of variables of the optimization problem is *n*.

$$W_k = \left[w_{i_1,j}, w_{i2,j}, \ldots, w_{i_n,j}\right] \quad (3)$$

Each weight to be optimized is represented by $w_{i_n,j}$. Thus, the objective function of the PSO integrated into the proposed ANN for the EMM is defined by equation (4).

$$F_{min\,RMSE} \rightarrow \frac{\sum_{n=0}^{N}\left(o_{t_n} - o_{p_n}\right)^2}{N} \quad (4)$$

Where o_{t_n} is the target output value of the *n* data, o_{p_n} is the predicted output value of the same *n* data, and N is the total number of available training data. According to the definition of the PSO algorithm [44] in each iteration, the particles find an optimal global solution called g_{best}. It is the best-obtained value of the objective function evaluated for each particle (of the total iterations made up to that moment). The best tracking value for each particle is called best personal p_{best}. The speed update and the search for these optimal solutions (for each particle) is given by equation (5).

$$v_n = w * v_n + c_1 rand(x) * (g_{best,n} - x_n) + c_2 rand(x) * (p_{best,n} - x_n) \tag{5}$$

Where the n particle speed is determined by v_n, the inertia factor by w and the acceleration constants are represented by $c_1$and c_2.

Proposed Energy Management Model (EMM)

The proposed EMM was designed to operate on an AC microgrid consisting of a photovoltaic solar array, a storage system, and a generation unit comprised of a BGP and a Genset. The election of the type of ANN and optimization algorithm used in this research is based as a continuation of previous work of the authors [23],where an optimized ANN-based model for a BGP is presented and compared against other traditional ANN models. Figure 7 shows the general structure of the proposed EMM. The continuous lines represent the Energy flows, and the discontinuous ones are the communication bus.

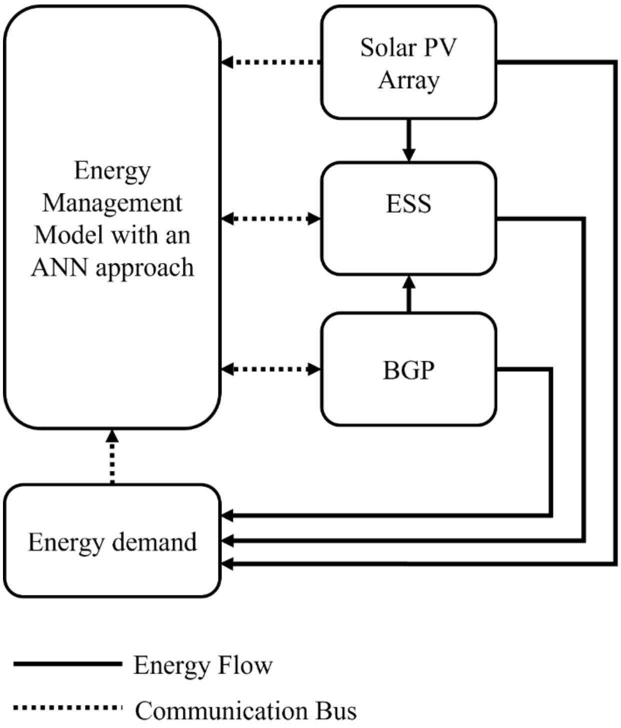


Figure 7. Overall structure of the proposed Energy Management Model.

As shown in Figure 7, the EMM is a central controller that collects information from the power generation and the backup sources, and the energy consumption to be supplied. The flow of information is unidirectional between the EMM and the solar PV array, while the communication between EMM, the storage system, and BGP is bidirectional. In this case, the PV data information only sends solar irradiation and power generation data. The stages followed to design the proposed EMS are shown in Figure 8. The overall methodology is divided into three main stages.

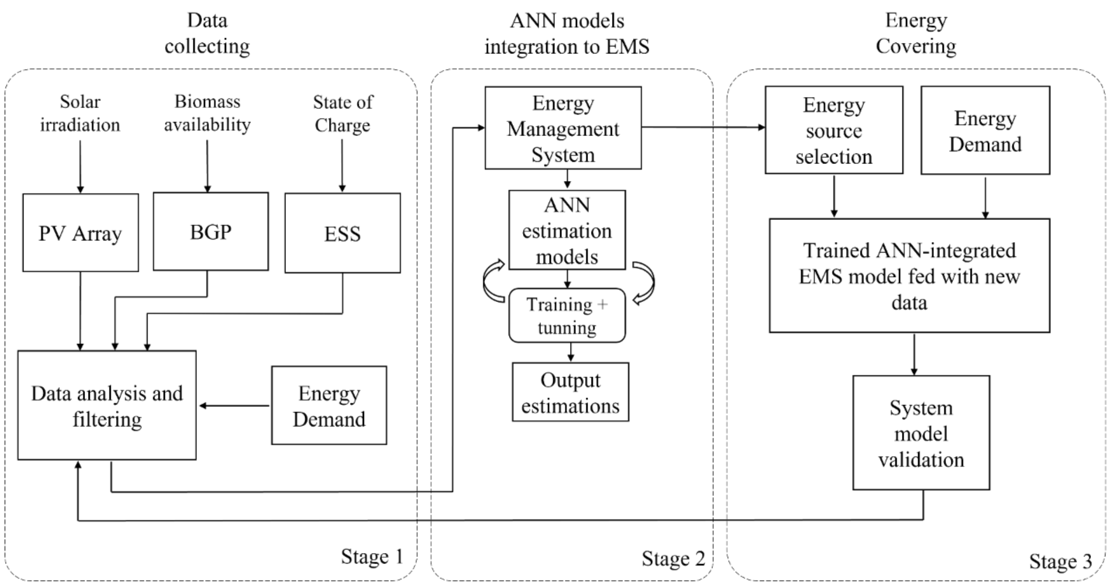


Figure 8. Overall methodology stages for integrating ANN models into the proposed EMS.

As shown previously in Figure 8, Stage 1 collects data from the multiple energy generation and the ESS backup units. Data collected from the solar PV array are solar irradiation and power generation. This information is collected and transmitted to a central controller through a power meter (PM) and a solar cell. Data from the BGP is gathered by a set of the PM and gas, the airflow meters, and the gas analyzers to determine the syngas mixture composition used. The BGP acts as an energy backup source when the storage system runs out of energy, and there is an unsupplied amount of power from renewable sources. The BGP could cover the energy uncovered energy demand. When energy from renewable sources exceeds the energy demand, this energy is stored in the batteries. A PM measures the energy demand. The last operation in Stage 1 is to data filtering and conditioning to be sent to the central controller that operates accordingly to the proposed EMM.

In the design of ANN, the normalization of the data is desirable to obtain better results. Normalization consists of adjusting the ranges of the ANN input values between [0,1] or [-1,1]. If the data is not normalized at the input, the ANN may have undesirable performance because not all network entries have a defined range of values; different values can be obtained in magnitude and reason change. Therefore, the optimal and desirable scenario is that all inputs and outputs are within a standard-length range. The methodology for working on an ANN with standardized data is sown in Figure 9.

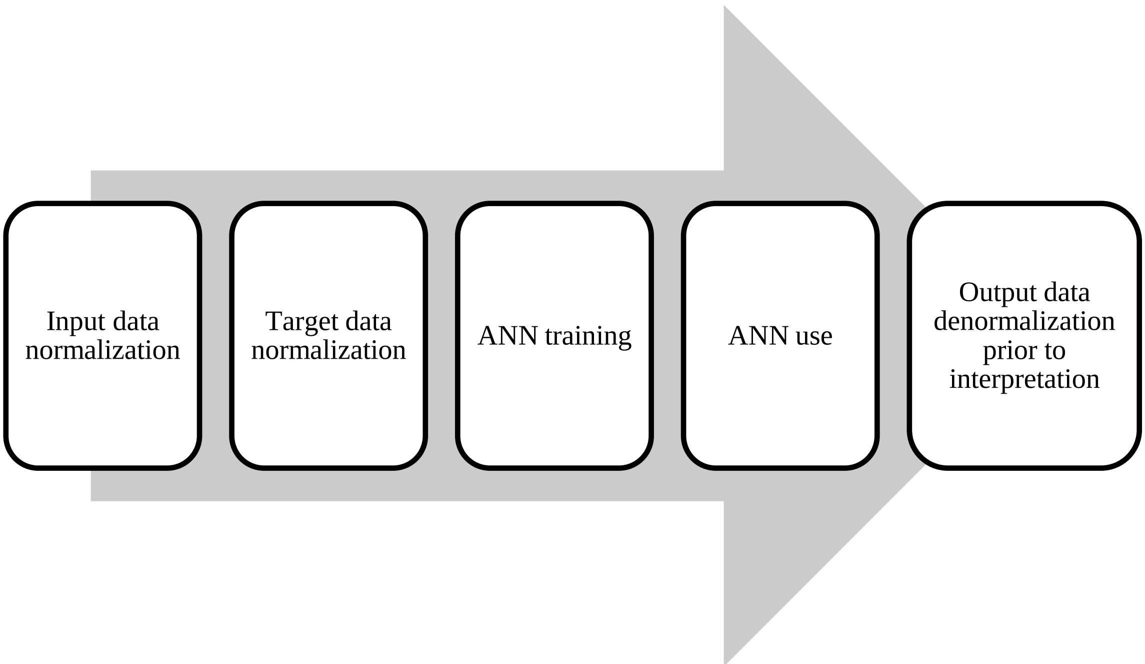


Figure 9. Training and use of a normalized-data ANN.

An ANN that has been trained with normalized data will deliver normalized data to its output, so once the results are obtained, these must be denormalized. The data transformation by the min-max normalization [45] defined by (6) for each input data, have been used in this work.

$$x'_i = (max_{scale} - min_{scale}) \cdot \left[\frac{(x_i - min_{val})}{(max_{val} - min_{val})}\right] + min_{scale} \tag{6}$$

Where,

x'_i is the i normalized input.

x_i is the i input.

max_{scale} is the maximum value of the range to be applied to the inputs.

min_{scale} is the minimum value of the range to be applied to the inputs.

max_{val} is the actual maximum value of the input dataset.

min_{val} is the actual minimum value of the input dataset.

To achieve uniformity in the training data, equation (6) was used with a value of 1 for max_{scale} and 0 for min_{scale}, with which all the magnitudes of the data were normalized on a scale of 0 to 1.

In Stage 2, all data are sent to the EMM of the MG central controller. The EMM can estimate the uncovered energy from the renewable energy sources and the storage system through an optimized Cascade Forward Propagation Artificial Neural Network (CFP-ANN), according to actual environmental conditions the profile of the consumer load demand. The CFP-ANNs used for the EMM are optimized using a PSO algorithm to find the best combination of weights and bias during the CFP-ANN. The performance of the optimized ANN is evaluated in terms of the Mean Squared Error (MSE) and linear regression analysis. The main objective of Stage 2 is to estimate outputs of the proposed ANN-based model to predict uncovered energy from renewable sources and the storage system and the necessary biomass and airflow to produce syngas and generate power from the BGP to cover this energy deficit.

Finally, Stage 3 is setup for Energy Covering. The EMM uses the ANN output estimations to select the energy source in this stage. The off-grid MG balance of the total active power is expressed in (7).

$$P_{apc}(t) = P_{load}(t) - P_{PV}(t) - P_{ESS}(t) - P_{BGP}(t) \tag{7}$$

Where $P_{apc}(t)$ is the active power covered by the MG in off-grid operation mode, $P_{load}(t)$ is the energy demand, $P_{PV}(t)$ is the power delivered by the PV array, $P_{ESS}(t)$ is the power from the ESS, and $P_{BGP}(t)$ is the power coming from the BGP.

The EMM constraint equations that define the operational limits are shown from (8) to (11).

$$-P_{PV\min} \leq P_{PV}(t) \leq P_{PV\max} \tag{8}$$

$$-P_{ESS\min} \leq P_{ESS}(t) \leq P_{ESS\max} \tag{9}$$

$$SoC_{\min} \leq SoC(t) \leq SoC_{\max} \tag{10}$$

$$-P_{BGP\min} \leq P_{BGP}(t) \leq P_{BGP\max} \tag{11}$$

Equation (8) denotes the constraints of the power obtained from the solar PV array, (9) to the output power of the storage system constraint, (10) to the storage system SoC constraint, and (11) the constraints of the power delivered by the BGP. The $P_{BGP}(t)$ power delivered by the BGP depends on the mixture of air and syngas in the electric generator and the heating value of the syngas, which in turn depends on its composition. All these considerations are integrated into the ANN involved in the proposed EMM. The energy source selection is executed by the EMM using a set of rules that consider the ANN predicted outputs. The EMM measurement and data flow are shown in Figure 10.

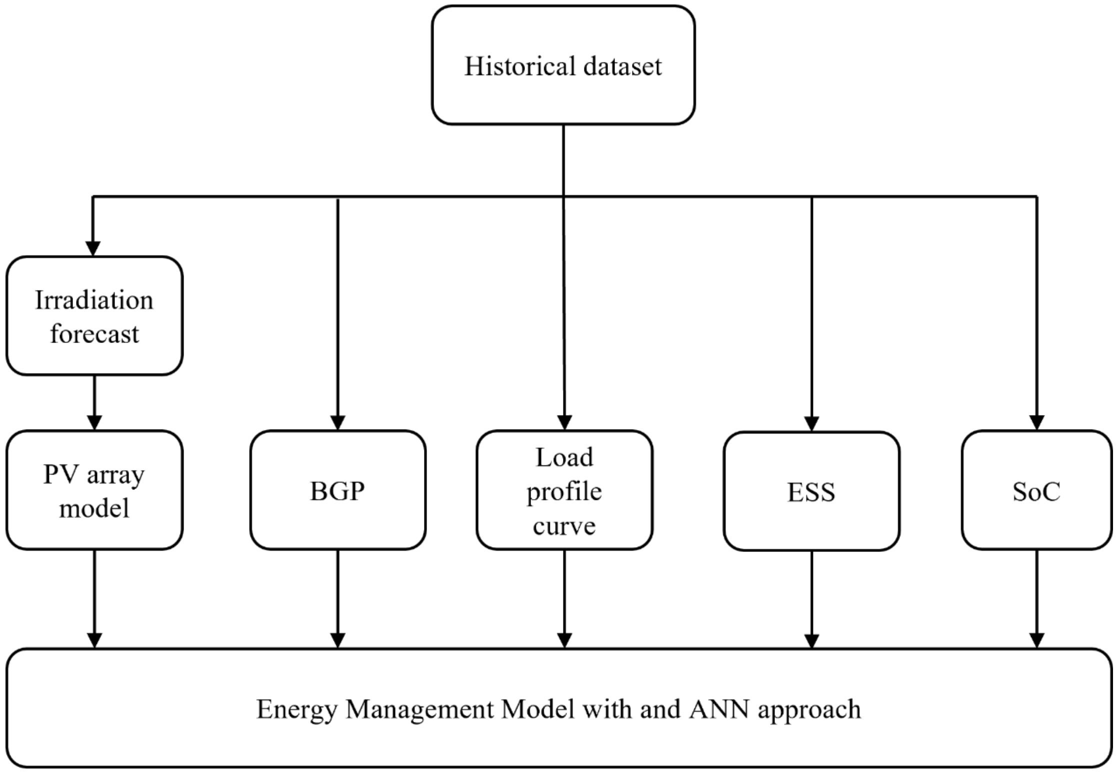


Figure 10. EMM measurement and data flow.

Simulation and Training

The proposed EMM was designed and implemented on MATLAB and Simulink, measured data from experimental tests of the microgrid located in the renewable energy laboratory of the Polytechnic University of Valencia were used to carry out simulations. Since the proposed model integrates ANN algorithms, a training phase is required. A total of 230,760 data were used for ANN training. Part of the TRAINING of the ANN consists of reducing the error between the outputs of the ANN and a set of objective values. To achieve this, the PSO algorithm was implemented to obtain the optimal values of weights and bias of the trained neural network. Table 6 shows the hardware used for the simulations, and Table 7 shows the ANN type and tuning parameters configured into the PSO algorithms.

Table 6. Hardware configuration of simulation platform for the proposed EMM.

Hardware	**Characteristics**
CPU	Intel Core i7-6700 @ 2.8 GHZ
RAM	16 GB DDR3 2133 MHZ
SSD	560 MBS / 520 MBS

Table 7. ANN and PSO parameters configuration for the proposed EMM.

Parameters	Adjust
Type of ANN	Feed -Forward Neural Network
Training algorithm	Particle Swarm Optimization
Population of particles	600
C1	2.5
C2	1.5
Function for performance	Mean Squared Error
Number of Input Neurons	6
Number of Hidden Layer	1-50
Number of Output Neurons	5
Learning Iterations	1000

The learning algorithm used in the ANN integrates the PSO, and to determine the error in the output of the ANN the MSE according to equation (12) was used.

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(O_{predicted} - O_{target}\right)^2 \tag{12}$$

Where $O_{predicted}$ represents the output from the ANN and O_{target} is the target data taken from the experimental dataset and N is the total number of samples.

Different simulation scenarios were used for various operating conditions in the microgrid, varying energy demand, and energy availability from sources. The validation of the proposed EMM was done for two cases, with different conditions of disposal of renewable energy in the MG and different conditions state of charge of the storage system. For both case studies, a standard demand curve was considered, typical of the application of MG taken as a model. In Table 8 can be seen the summary of the values of the storage system parameters used for each simulation under different environmental conditions.

Table 8. Value of initial parameters of the storage system.

Parameter	Value
Battery number	24
Roundtrip battery efficiency	90%
Battery nominal voltage	2 V
Battery capacity	210 Ah
Initial SoC	90%
Capacity (kWh)	10.1

Variable correlation

Prior to the simulation of the model, and its evaluation, it is important to perform a correlation analysis of the variables involved. Correlation is a statistical technique that allows to measure the level of relationship that exists between two or more variables [46], this allows to determine the level of interference that each variable has in each stage of the model.

There are several techniques for calculating correlation coefficients, within these methods are the Pearson Correlation, and the Spearman Correlation [47]. Pearson's method requires data to have a normal distribution, while Spearman's method does not require this condition [48]. In the present work, the Anderson-Darling normality test method has been used, considering a p-value of significance of 0.05, to determine the normality of the variable dataset at each stage of the model. If the p-value of significance is less than 0.089 then the dataset is considered to have a normal distribution [49], and then Pearson's correlation method is applied.

Once the normality of the data has been determined and the correlation coefficients calculated, it is possible to perform a significance analysis between the variables. The correlation coefficient can have values from -1 to 1, determining the relationship strength between two or more variables as detailed in Table 9.

Table 9. Strength correlation coefficient interpretation.

From	To	Correlation strength
± 0.00	± 0.09	Null
± 0.10	± 0.19	Very weak
± 0.20	± 0.49	Weak
± 0.50	± 0.69	Moderate
± 0.70	± 0.84	Significant
± 0.85	± 0.95	Strong
± 0.96	±1.00	Perfect

A negative correlation coefficient indicates that the variables are related to an inverse manner, that is, when one variable has a high value the other has a low value, the closer to -1 the value of the correlation coefficient, the clearer the extreme covariance, and therefore we will have a force of correlation, and covariance, very strong or perfect.

When the correlation coefficient is equal to zero or very close, we have a null or very weak correlation, which means that it is not possible to determine any sense of covariation between the variables.

If the correlation coefficient is equal to, or very close to, 1 positive, we have a strong or perfect positive correlation, and covariance.

Results

Variable correlation analysis

Since the EMM proposed in this paper is based on a cascade model of ANNs, three covariance analyses have been performed for the variables involved in each of the three layers of the EMM. The first step in calculating the correlation coefficient between the variables in the model is to determine whether the dataset has a normal distribution or not, the results are detailed below.

Data normality test

To determine the normality of the data, the Anderson-Darling Normality Test technique was used. It was determined that both the conjunct of data of the first, the second and the third layer have a normal distribution according to the criterion of the Anderson-Darling test, since all variables in all layers of the model have a p-value less than 0.05, so it is possible to perform a correlation analysis using Pearson's method.

Variable correlation analysis

Once it was found that the variables of the model follow a normal distribution, Pearson's method was applied to determine the correlation coefficients between each variable in each of the three layers of the EMM. The matrices obtained by the Pearson method for correlation coefficients are shown in Table 10 to Table 12, for the first, second and third layer of the EMM, respectively. In the tables mentioned, as the value of the correlation coefficient is closer to 1 it will be highlighted of a more intense green color, and the closer it is to -1 it will be highlighted in a more intense blue color, for values close to 0 the color will be more subdued. The output variables of each EMM layer are highlighted in bold text.

Table 10. EMM first layer correlation coefficient matrix.

Coefficient	Hour	Irradiation	**PV Gen.**
Hour	1.00	-0.11	-0.12
Irradiation		1.00	0.98
PV Gen.			1.00

As can be seen in Table 10 above, the most significant variable for the generation of energy by the PV array is solar irradiation, considering the time window in which the data set was evaluated, so it has low negative correlation coefficient value (-0.11). A perfect positive correlation between irradiation and power generation of the PV array was observed (0.98).

Table 11. EMM second layer correlation coefficient matrix.

Coefficient	PV Gen.	ESS power	Energy demand	Uns. Energy	Freq.	P.F.	E.D. BGP	SoC	ESS P. delivery
PV Gen.	1.00	0.06	-0.02	-0.33	-0.10	-0.10	-0.36	-0.18	0.09
ESS power		1.00	-0.14	-0.34	-0.66	-0.66	-0.54	0.50	0.99
Energy demand			1.00	0.65	0.54	0.54	0.78	-0.65	-0.18
Uns. Energy				1.00	0.50	0.51	0.77	-0.45	-0.37
Freq.					1.00	1.00	0.80	-0.89	-0.72
P.F.						1.00	0.80	-0.89	-0.72
E.D. BGP							1.00	-0.71	-0.59
SoC								1.00	0.55
ESS P. delivery									1.00

Thanks to the correlation matrix for the second layer of the EMM, shown in Table 11, a covariance analysis can be performed between input variables and output variables.

For the output variable of the energy demand (ED) to the BGP strong positive correlation coefficients (cc) are observed with the electrical parameters such as frequency ($cc = 0.80$) and power factor ($cc = 0.80$) of the electrical signal as well as a significant cc with the energy demand ($cc = 0.78$); in addition to moderate negative correlation with the power delivered by the ESS ($cc = -0.59$) and a significant cc to its SoC ($cc = -0.71$). That means that the energy demand to the BGP depends directly on the energy to the MG, and its inverse to the ESS capacity and its SoC. Meanwhile the SoC shows a moderate positive cc with the ESS power delivery ($cc = 0.55$), a moderate negative cc to the energy demand to the MG ($cc = -0.65$) and significant negative cc to ED to BPG ($cc = -0.71$). For the ESS power delivery it depends highly on its actual capacity as can be constated with its $cc = 0.99$, and a moderate cc to the SoC ($cc = 0.55$).

Table 12 EMM third layer correlation coefficient matrix

Coefficient	E.D. BGP	SoC	ESS P. delivery	CH_4 %	CO_2 ppm	CO %	H_2 %	N_2 ppm	Biomass Q	Syngas Q	Air Q	P. BGP	Uns. Energy
E.D. BGP	1.00	-0.71	-0.59	0.79	0.80	0.80	0.79	0.80	0.88	0.91	0.75	0.99	0.77
SoC		1.00	0.55	-0.88	-0.89	-0.89	-0.88	-0.89	-0.86	-0.77	-0.82	-0.75	-0.45
ESS P. delivery			1.00	-0.72	-0.72	-0.72	-0.72	-0.72	-0.70	-0.65	-0.67	-0.61	-0.37
CH_4 %				1.00	0.99	0.99	0.98	0.99	0.96	0.86	0.91	0.83	0.49
CO_2 ppm					1.00	1.00	0.99	1.00	0.96	0.87	0.92	0.84	0.50
CO %						1.00	0.99	1.00	0.96	0.87	0.92	0.83	0.52
H_2 %							1.00	0.99	0.96	0.86	0.92	0.83	0.51
N_2 ppm								1.00	0.97	0.87	0.92	0.84	0.51
Biomass Q									1.00	0.96	0.96	0.91	0.60
Syngas Q										1.00	0.93	0.92	0.65
Air Q											1.00	0.79	0.48
P. BGP												1.00	0.70
Uns. Energy													1.00

As can be seen in Table 12 above, the correlation coefficient matrix for the third layer of the model has clearly delimited zones for very positive (close to 1) and very negative coefficients (close to -1). This gives us indications of the strong covariance, and therefore correlation, existing in each of the input and output variables in this layer of the model. All the output parameters of the BGP have a strong positive *cc* for the input variables, which are mostly flows of biomass, air, syngas, and the composition of the syngas, which affects the calorific value of the same and therefore the amount of energy that can be extracted from it. While the output power of the BGP is inversely proportional to the SoC and the capacity of the ESS as highlighted by the blue zones of the correlation coefficient matrix with moderate to significant negative *cc* values.

ANN performance

An EMM for an off-grid microgrid through particle swarm optimization and artificial neural networks approach was developed in this work to effectively manage the energy supply from a renewable base microgrid to a load. The proposed model considers as generation units a solar PV array and a BGP that operates as a backup. The PV array and the BGP can supply energy to the load or the storage system.

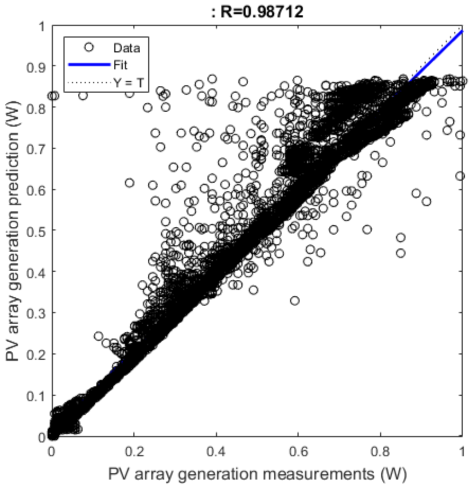
The integrated ANN EMM inputs are time, solar irradiation, load profile, calculated RES unserved power according to load demand, storage system power (input and output), syngas composition, frequency, and power factor. The predicted outputs are, on the one hand, the PV array generation, SoC, ESS charge/discharge power (according to the estimated power balance) and, on the other hand, from the BGP side are mass flow M, syngas flow Q_{syngas} and airflow $Q_{air_{ICE}}$. After the ANN estimations, the delivered power P_d and uncovered power P_u are calculated by the EMM, and the ANN outputs fed the EMM rules to manage the BGP operation inside the MG.

For the ANN training, a total of 480 simulations were carried out to find the best weight and bias configuration to predict the desired outputs from the ANN-based EMM using a 115,360 measurements dataset for each case. The summary of the best results of RMSE and the correlation coefficient R are shown in Table 13.

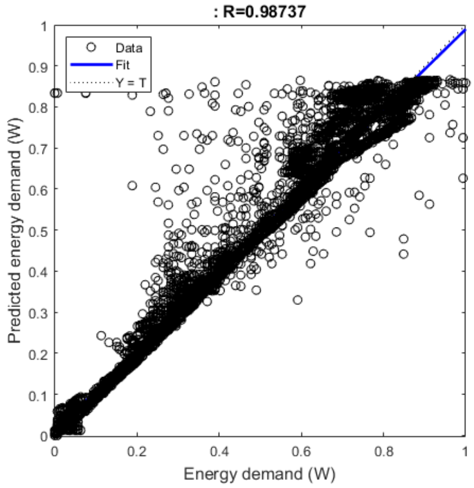
Table 13. Summary of MSE and linear regression of the trained ANN.

Parameter	**ANN model**	
	RMSE	R
Biomass flow (M)	0.0465	0.9944
Syngas generation$\left(Q_{syngas}\right)$	0.0393	0.9996
Airflow into the ICE $\left(Q_{air_{ICE}}\right)$	0.1194	0.9997
Power demand to BGP (P_d)	0.0513	0.9873
Power delivered by BGP(P_{SGPP})	0.0342	0.9810
PV array power generation $(PV_{Generation})$	0.0303	0.9871
Storage System State of Charge (SoC)	0.0419	0.9850
storage System power delivery $\left(BB_{power}\right)$	0.0212	0.9960
Unserved energy prediction (P_u)	0.0513	0.9716

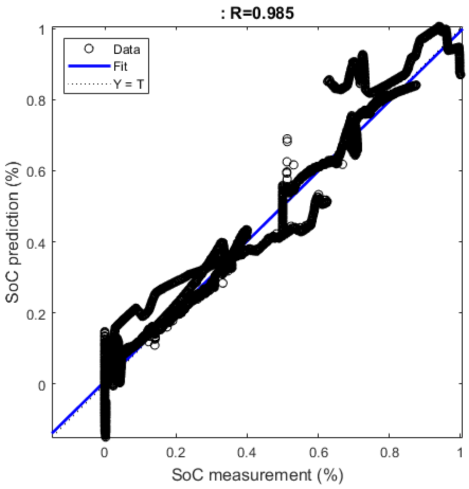
The R value from the linear regression analysis for the ANN model output indicates the performance of the trained ANN for each variable. R and linear regression plot of the ANN for each layer obtained from the ANN-based model are shown in Figure 11.



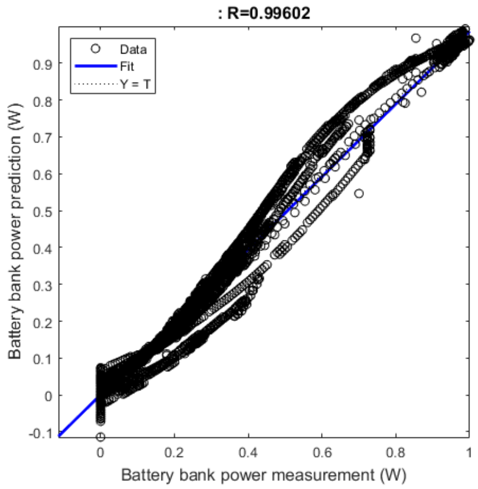
(a) PV generation prediction.



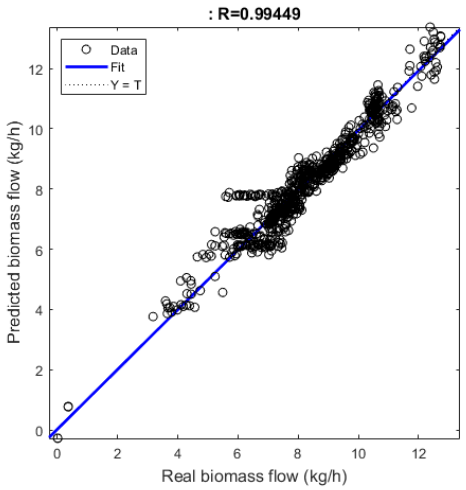
(b) Energy demand prediction.



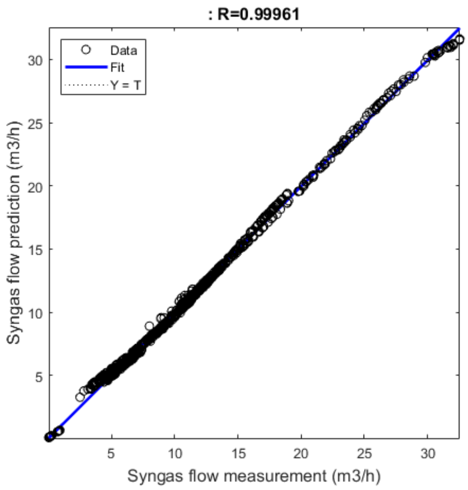
(c) SoC prediction.



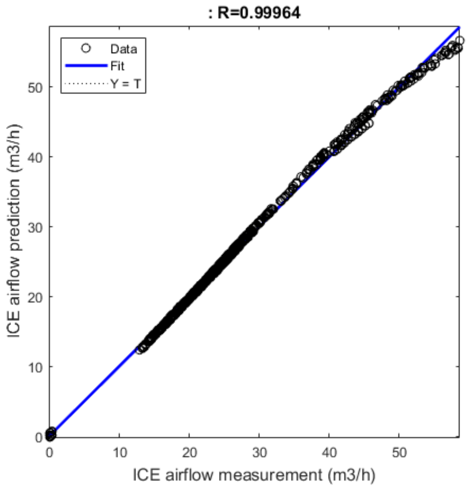
(d) SS power prediction.



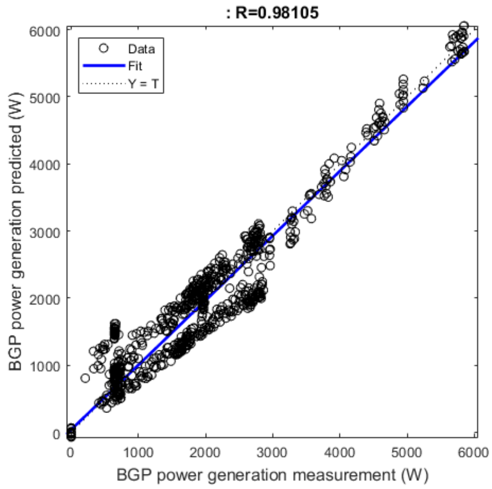
(e) Biomass flow prediction.



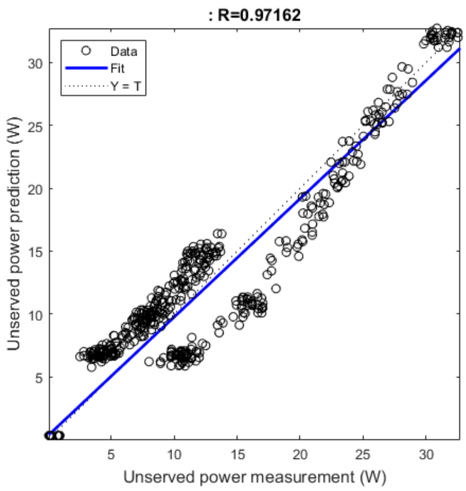
(f) Syngas flow prediction.



(g) ICE airflow prediction.



(h) BGP power generation prediction.



(i) Unserved power prediction.

Figure 11. Linear regression plots from the ANN model predicted parameters. (a) is the output of the first ANN layer, (b) to (d) are the outputs of the second ANN layer, and (e) to (i) are the third ANN layer outputs.

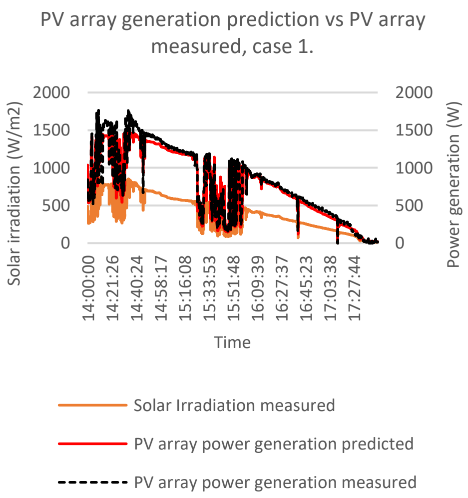
Linear regression graphs of the training outcome of ANNs have characteristic shapes that depend on various factors. Among the factors that are related in their form and proximity to a value of R = 1 are the amount of data that was available for the training of the ANN as well as the strength of the relationship between the variables selected as input and output for the training stage.

The Figure 11 (a, and b) have very similar shapes due to that both output variables depend on a similar and periodic set of training data. The greater the amount of data, the better linear regression we will have at the output of the ANN, as well as the strength of the relationship between the input and output variables, that is, the closer to 1 or -1 the correlation coefficient between them, depending on whether there is a direct or inversely proportional relation between the variables, see Figure 11 (d, f and g) were R coefficient is higher than 0.99. When a set of variables is chosen as input, and they most of them have a weak relation between them then a worst linear regression will be, see Figure 11 (a, b, c, h, and i).

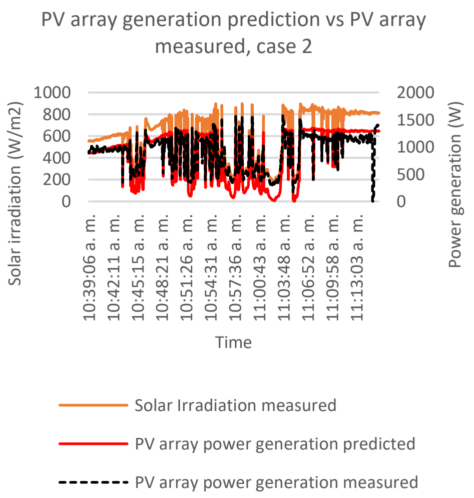
In some cases, the linear regression plot can show a double, or diverse, tendency line, as shown in Figure 11 (c, d, and i). In the SoC, Figure 11 (c), prediction linear regression plot a multiple tendency is observed due to that only two of the nine involved variables have a moderate positive cc value, that is the ESS power delivery ($cc = 0.55$) and the ESS capacity ($cc = 0.50$), this causes the ANN of this layer to get confused on the output prediction, to avoid this undesired effects it is needed to consider more related variables that are often difficult to measure in experimental MG since they need specialized devices. The same analysis can be performed in Figure 11 (d) for the ESS power predictions were the only positive cc are the ESS capacity (cc=0.99) and a moderate cc for the SoC ($cc = 0.55$). For the unserved energy prediction, Figure 11 (i), the double tendency line of the linear regression can be explained since there are only two variables (out of 13) with positive correlation coefficients, in this case only the input variable of the energy demand to the BGP has a significant cc strength with $cc = 0.77$ and the BGP power generated with $cc = 0.70$.

EMM test

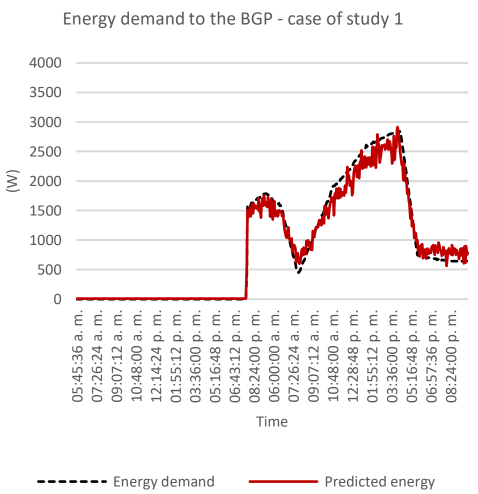
Once the EMM was designed and an evaluation of its performance was carried out based on covariance analysis of variables and linear regression plots, it was proceeded to perform a test of the model using real data to obtain estimations. The EMM was tested under two scenarios, a case 1 and a case 2, where different demand curves to the MG and different environmental conditions were used. The results obtained for the main parameters of interest are shown in the graphs in Figure 12.


PV array generation prediction vs PV array measured, case 1.
Solar irradiation (W/m2)
Power generation (W)
Time
Solar Irradiation measured
PV array power generation predicted
PV array power generation measured

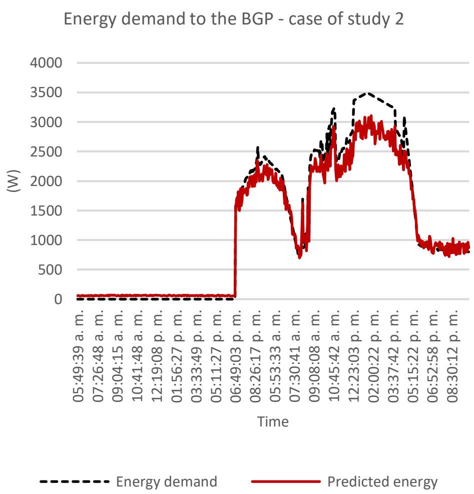
(a)


PV array generation prediction vs PV array measured, case 2
Solar irradiation (W/m2)
Power generation (W)
Time
Solar Irradiation measured
PV array power generation predicted
PV array power generation measured

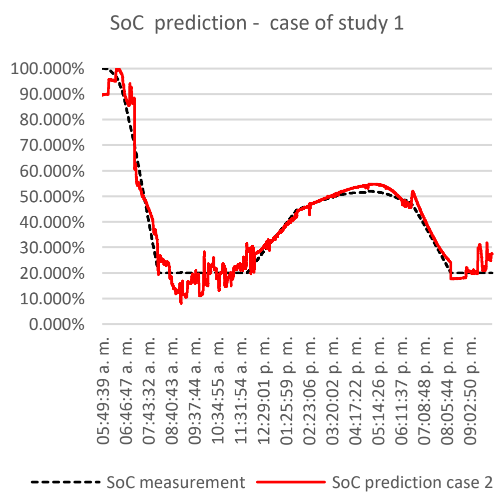
(b)


Energy demand to the BGP - case of study 1
(W)
Time
Energy demand
Predicted energy

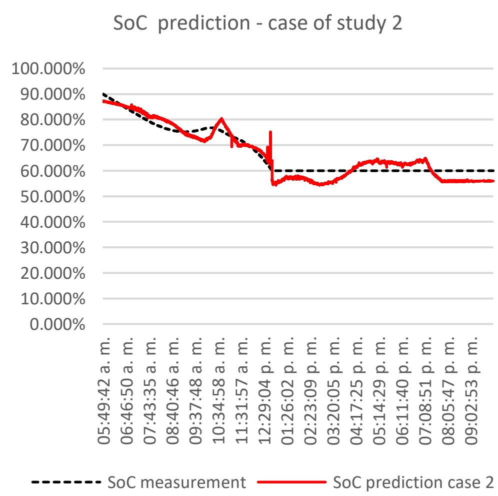
(c)


Energy demand to the BGP - case of study 2
(W)
Time
Energy demand
Predicted energy

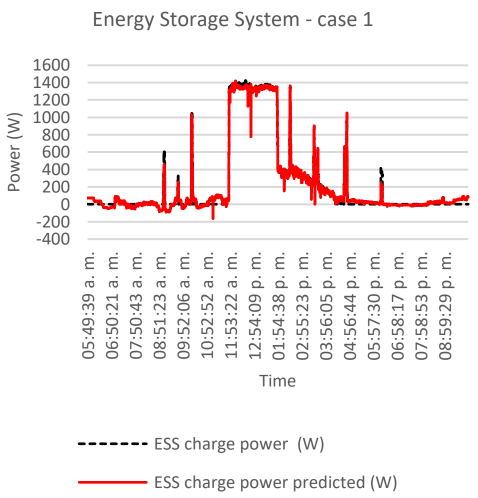
(d)


SoC prediction - case of study 1
SoC measurement
SoC prediction case 2

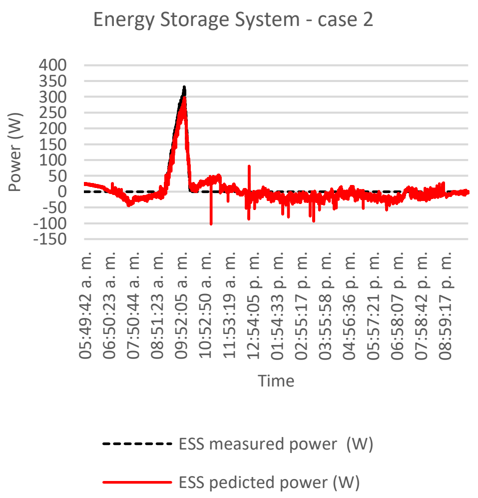
(e)


SoC prediction - case of study 2
SoC measurement
SoC prediction case 2

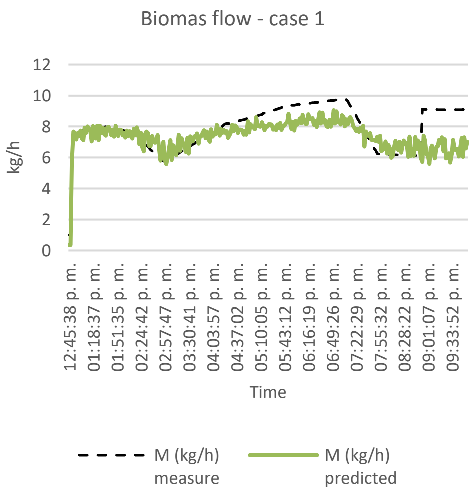
(f)


Energy Storage System - case 1
Power (W)
1600
1400
1200
1000
800
600
400
200
0
-200
-400
05:49:39 a. m.
06:50:21 a. m.
07:50:43 a. m.
08:51:23 a. m.
09:52:06 a. m.
10:52:52 a. m.
11:53:22 a. m.
12:54:09 p. m.
01:54:38 p. m.
02:55:23 p. m.
03:56:05 p. m.
04:56:44 p. m.
05:57:30 p. m.
06:58:17 p. m.
07:58:53 p. m.
08:59:29 p. m.
Time
ESS charge power (W)
ESS charge power predicted (W)

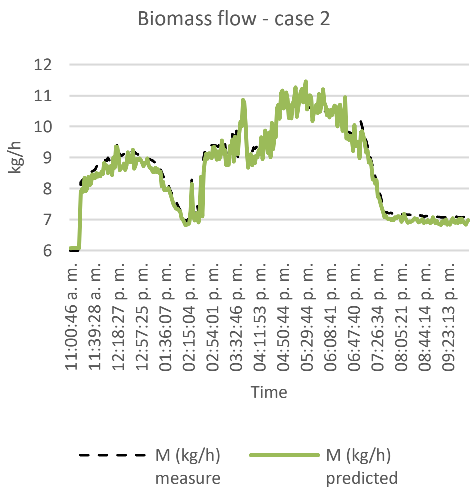
(g)


Energy Storage System - case 2
Power (W)
400
350
300
250
200
150
100
50
0
-50
-100
-150
05:49:42 a. m.
06:50:23 a. m.
07:50:44 a. m.
08:51:23 a. m.
09:52:05 a. m.
10:52:50 a. m.
11:53:19 a. m.
12:54:05 p. m.
01:54:33 p. m.
02:55:17 p. m.
03:55:58 p. m.
04:56:36 p. m.
05:57:21 p. m.
06:58:07 p. m.
07:58:42 p. m.
08:59:17 p. m.
Time
ESS measured power (W)
ESS pedicted power (W)

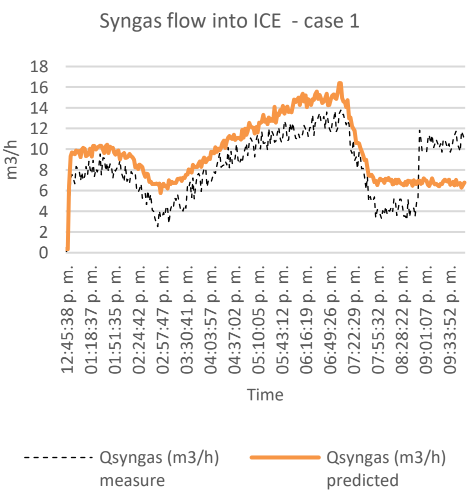
(h)


Biomas flow - case 1
kg/h
12
10
8
6
4
2
0
12:45:38 p. m.
01:18:37 p. m.
01:51:35 p. m.
02:24:42 p. m.
02:57:47 p. m.
03:30:41 p. m.
04:03:57 p. m.
04:37:02 p. m.
05:10:05 p. m.
05:43:12 p. m.
06:16:19 p. m.
06:49:26 p. m.
07:22:29 p. m.
07:55:32 p. m.
08:28:22 p. m.
09:01:07 p. m.
09:33:52 p. m.
Time
M (kg/h) measure
M (kg/h) predicted

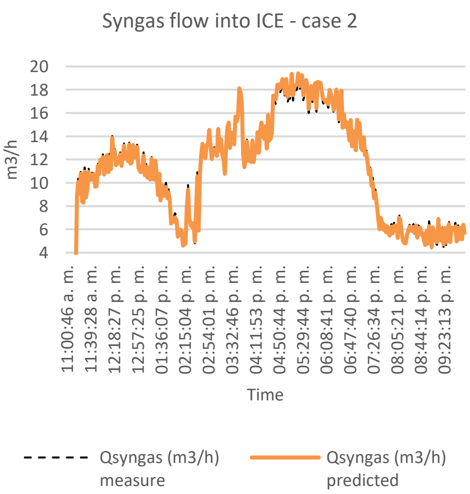
(i)


Biomass flow - case 2
kg/h
12
11
10
9
8
7
6
11:00:46 a. m.
11:39:28 a. m.
12:18:27 p. m.
12:57:25 p. m.
01:36:07 p. m.
02:15:04 p. m.
02:54:01 p. m.
03:32:46 p. m.
04:11:53 p. m.
04:50:44 p. m.
05:29:44 p. m.
06:08:41 p. m.
06:47:40 p. m.
07:26:34 p. m.
08:05:21 p. m.
08:44:14 p. m.
09:23:13 p. m.
Time
M (kg/h) measure
M (kg/h) predicted

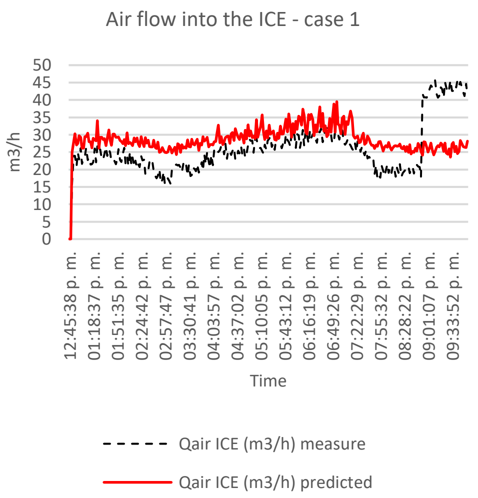
(j)


Syngas flow into ICE - case 1
m3/h
18
16
14
12
10
8
6
4
2
0
12:45:38 p. m.
01:18:37 p. m.
01:51:35 p. m.
02:24:42 p. m.
02:57:47 p. m.
03:30:41 p. m.
04:03:57 p. m.
04:37:02 p. m.
05:10:05 p. m.
05:43:12 p. m.
06:16:19 p. m.
06:49:26 p. m.
07:22:29 p. m.
07:55:32 p. m.
08:28:22 p. m.
09:01:07 p. m.
09:33:52 p. m.
Time
Qsyngas (m3/h) measure
Qsyngas (m3/h) predicted

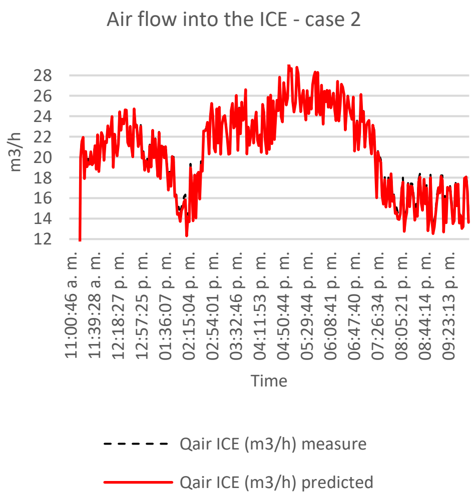
(k)


Syngas flow into ICE - case 2
m3/h
20
18
16
14
12
10
8
6
4
11:00:46 a. m.
11:39:28 a. m.
12:18:27 p. m.
12:57:25 p. m.
01:36:07 p. m.
02:15:04 p. m.
02:54:01 p. m.
03:32:46 p. m.
04:11:53 p. m.
04:50:44 p. m.
05:29:44 p. m.
06:08:41 p. m.
06:47:40 p. m.
07:26:34 p. m.
08:05:21 p. m.
08:44:14 p. m.
09:23:13 p. m.
Time
Qsyngas (m3/h) measure
Qsyngas (m3/h) predicted

(l)



(m)



(n)

Figure 12. Plots of test carried out for the EMM. In (a) and (b) the PV array generation for case 1 and 2 are shown. In (c) and (d) the Energy demand to BGP for case 1 and 2 are shown. In (e) and (f) the ESS SoC estimation for case 1 and 2 are shown. In (g) and (h) the ESS power for case 1 and 2 are shown. In (i) and (j) the Biomass flow to BGP for case 1 and 2 are shown. In (k) and (l) the Syngas flow into the ICE for case 1 and 2 are shown. And, in (m) and (n) the Airflow into the ICE for case 1 and 2 are shown.

As can been seen in the above Figure , in some cases there is a better fit between predicted and real data for case 2, this is caused due to that the EMM used for case 2 was also trained with case 1 data. In Table 14, a summary of the EMM performance indicators is shown.

Table 14. Summary of RMSE values from study case 1 and study case 2

	Case 1			Case 2		
	RMSE	**R**	**MSD**	**RMSE**	**R**	**MSD**
PV array generation	0.0303	0.9871	0.0159	0.0520	0.9871	0.0763
Energy demand to BGP	0.0513	0.9873	0.2085	0.0688	0.9873	0.2282
SS SoC	0.0419	0.9850	0.0210	0.0307	0.9850	0.0190
SS power	0.0277	0.9960	0.0139	0.0128	0.9960	0.0075
Biomass flow	0.2799	0.9944	0.4264	0.0443	0.9944	0.1609
Syngas flow	0.0583	0.9996	0.3503	0.0390	0.9996	0.1526
Air flow	0.9496	0.9997	4.5798	0.0585	0.9997	0.1786

As can be seen in Table 14, the EMM proposed in this work can estimate the main values of the EMS for an off-grid microgrid, for case 1 with which the model was tested, the lowest RMSE is in the estimation of the power in the ESS, being an RMSE of 0.0277, and the largest for the airflow with an RMSE of 0.9496, having the same behavior for the MSD, the lowest for the power of the batteries with a value of 0.0139 and the highest for the airflow. As for case 2, with which the EMM was tested; the lowest RMSE is equal for battery power with a value of 0.0128 and the highest RMSE of 0.0688 for energy demand for the BGP; in terms of the MSD, the same behavior is observed with a value of 0.0075 and 0.2282 respectively. Besides, the R values from the linear regression analysis for the ANN model output indicate the trained ANN's great performance for each variable, being the lowest R value 0.9871 for the PV array generation and the highest R value 0.9997 for the airflow.

Conclusions

This work shows the results of the proposed EMM for a microgrid operating in off-grid mode, consisting of a PV solar array, an SS, and a BGP. The integration of an ANN in the dynamics model was tested to obtain the main parameter estimations of each subsystem. The primary objective of this proposed EMM is to increase the reliability and efficiency of the off-grid system, supplying energy to the load in case the RES and battery storage cannot meet that energy demand. Then the BGP must provide the required energy. The integrated cascade ANN architecture model consisted of a three-layer array of subnets; the last layer is recurrent to the second layer. The ANN model weights were optimized using the PSO algorithm. Once the model was created, the performance of the model was validated by making an analysis of the output data of the model. The output data were analyzed using linear regression graphs, and these were interpreted by a study of variable covariance to determine the correlation coefficient matrices in each layer of the proposed EMM model. For the first layer of the EMM, a direct positive correlation was found between the irradiation and the output power of the PV array ($cc = 0.98$), with which the ANN obtained a very good performance as expected. In the second layer of the EMM both negative and positive correlation coefficients were found, this indicates that there are variables with covariance both directly proportional and inversely proportional. In the case of the prediction of the SoC of the ESS, the ANN had certain difficulties in the prediction of the same, this can be seen in the graph of the linear regression of the SoC, where various trends are appreciated, the analysis of the correlation matrix for this output variable indicates that of the input variables only one of 9 has a positive correlation coefficient and is not especially strong ($cc = 0.55$), which indicates that to improve the model it is necessary to achieve a new set of input variables with a correlation closer to the SoC to obtain a better prediction of it by the ANN of the EMM.

After performing the analysis of the performance of the EMM, it was tested using real data and comparing with the prediction of the EMM before this data set, it was tested in two case studies varying the energy demand to the MG and the environmental conditions.

Two scenarios were evaluated, in the first scenario the model obtained an RMSE of 0.2056 and MSD of 0.8023, in the second scenario the RMSE was of 0.0437 and an MSD of 0.1176. The reduction of the RMSE and the MSD between scenarios is explained due to the ANN learning capabilities, second scenario was simulated using first scenario historical data to evaluate the improvement of the model as it is fed with more data. The average R coefficient obtained from the ANN based EMM model was 0.9927 considering all subnets involved, meanwhile the average RMSE is 0.1247 and the MSD of 0.4599. As a conclusion, using an ANN model built by three cascade subnets and with recurrence in the last layer is an effective alternative for the model of complex and dynamic electrical systems such as hybrid electric microgrids based on renewable energies, allowing the estimation of the main parameters that are used for energy management effectively.

As future work, it is planned to improve the model for the integration of more generation and storage subsystems, continue training the ANN using more experimental datasets to obtain the most optimal solutions for the management of RES in MGs, as well as an automated control system for their management and optimization.

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List of Acronyms

ANN	Artificial Neural Network
BGP	Biomass Gasification Plant
BP	Back Propagation
c_1	PSO particle personal acceleration coefficient
c_2	PSO particle social acceleration coefficient
cc	Correlation coefficient
CF-P	Cascade Forward Propagation
$CH_4[\%]$	Methane Percentage
CO_2	Carbon Dioxide
$CO_2[\%]$	Carbon Dioxide Percentage
CONACYT	Consejo Nacional de Ciencia y Tecnología
ΔP_{bed}	Fluidized bed pressure
E	Error
EBPGS	Energy Backup Power Generation Systems
EMM	Energy Management Model
EMS	Energy Management System
ESS	Energy Storage Systems
F	Frequency
F_{act_i}	ANN Activation Function
FF-BP	Feed Forward Back Propagation

FIS	Fuzzy Inference System
f_{min}	Objetive function to be minimized
F_{pro_n}	ANN Propagation Function
GA	Genetic Algorithm
Genset	Generator set (Generator + Alternator)
H_2[%]	Hydrogen Percentage
HRES	Hybrid Renewable Energy Systems
LabDER-UPV	Renewable Energies Laboratory at the Universitat Politènica de València
LHV	Lower Heating Value
ICE	Internal Combustion Engine
M	Biomass flow
MG	Microgrids
MLP	Multilayer-Perceptron
MSD	Mean standard deviation
MSE	Mean Squared Error
N	Number of samples
N_2	Nitrogen Percentage
o_{i_j}	ANN weighted output
$o_{predicted}$	Predicted Output
o_{target}	Target Output
P	Active Power
PF	Power Factor
PSO	Particle Swarm Optimization
PV	Photovoltaic

$Q_{air_{gasifier}}$	Reactor Airflow
$Q_{air_{ICE}}$	Internal Combustion Engine Airflow
Q_{syngas}	Syngas flow
R	Coefficient of determination
RBF	Radial Basis Function
RES	Renewable Energy Source
SS	Storage system
T_{env}	Environmental Temperature
T_1	Gassifier inlet temperature
TEG	Hybrid Thermoelectric Generator
v_n	PSO particle velocity function
$w_{i_1,j}$	Neuron weight
WTG	Wind Turbine Generator
X_i	Optimization variables vector
$Y_{predicted}$	ANN output prediction
Y_{target}	ANN target training value

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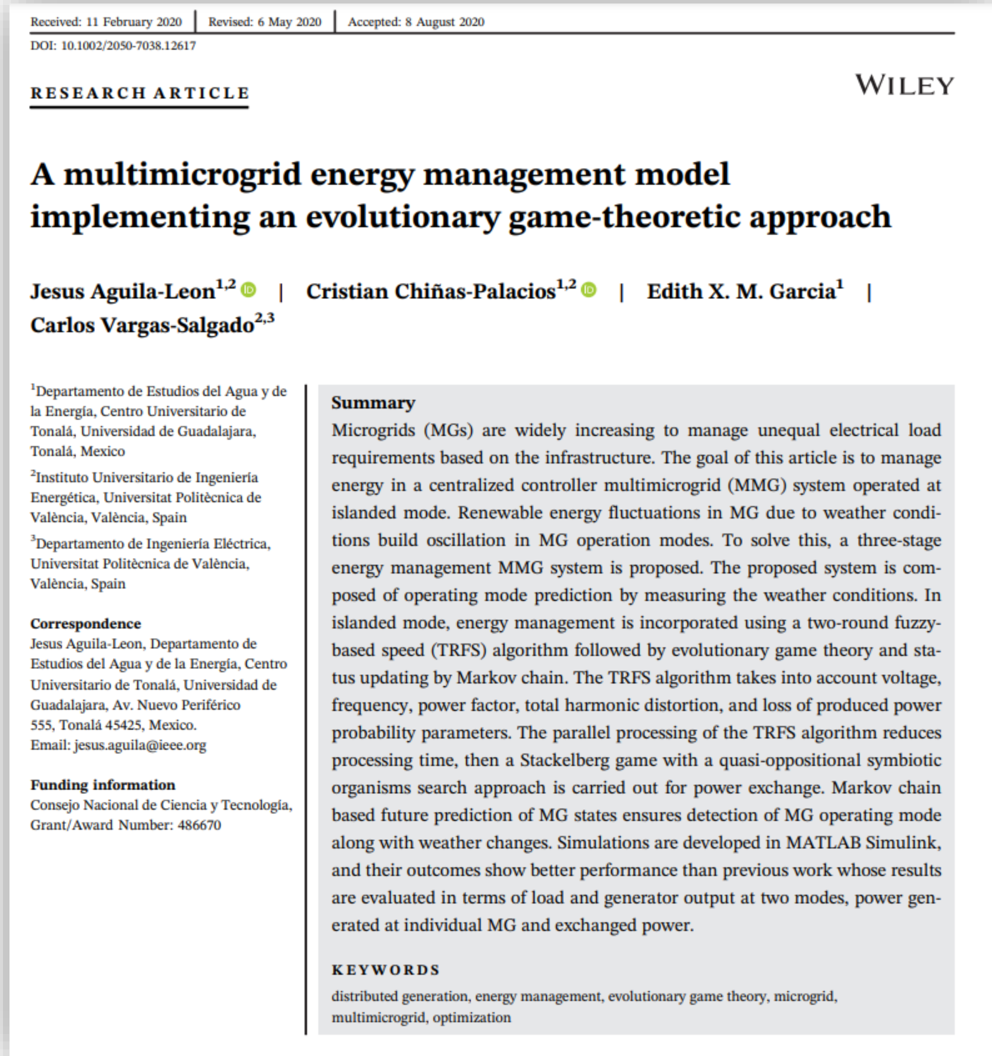
2.4 A multimicrogrid energy management model implementing an evolutionary game-theoretic approach



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RESEARCH ARTICLE

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A multimicrogrid energy management model implementing an evolutionary game-theoretic approach

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Summary
Microgrids (MGs) are widely increasing to manage unequal electrical load requirements based on the infrastructure. The goal of this article is to manage energy in a centralized controller multimicrogrid (MMG) system operated at islanded mode. Renewable energy fluctuations in MG due to weather conditions build oscillation in MG operation modes. To solve this, a three-stage energy management MMG system is proposed. The proposed system is composed of operating mode prediction by measuring the weather conditions. In islanded mode, energy management is incorporated using a two-round fuzzy-based speed (TRFS) algorithm followed by evolutionary game theory and status updating by Markov chain. The TRFS algorithm takes into account voltage, frequency, power factor, total harmonic distortion, and loss of produced power probability parameters. The parallel processing of the TRFS algorithm reduces processing time, then a Stackelberg game with a quasi-oppositional symbiotic organisms search approach is carried out for power exchange. Markov chain based future prediction of MG states ensures detection of MG operating mode along with weather changes. Simulations are developed in MATLAB Simulink, and their outcomes show better performance than previous work whose results are evaluated in terms of load and generator output at two modes, power generated at individual MG and exchanged power.

KEYWORDS
distributed generation, energy management, evolutionary game theory, microgrid, multimicrogrid, optimization

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En esta publicación se presenta el control terciario de la microrred con relación a otras microrredes y la red eléctrica. Se integran algoritmo de optimización y otras técnicas bio-inspiradas para la determinación del modo de operación de un conjunto de microrredes y el intercambio energético en las microrredes. El conjunto de microrredes consideradas se encuentra supervisada y gestionadas por un controlador central que considera parámetros medio ambientales y de demanda de energía para el establecimiento de modo de operación. Se integran además técnicas de lógica difusa para la toma de decisiones. El modelo propuesto se compara contra la literatura. La metodología y los principales resultados se detallan a continuación.

A Multi-Microgrid Energy Management Model Implementing an Evolutionary Game Theoretic Approach

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Abstract

Microgrids are widely increasing to manage unequal electrical load requirements based on the infrastructure. The goal of this paper is to manage energy in a centralized controller multi-microgrid system operated at islanded mode. Renewable energy fluctuations in microgrid due to weather conditions build oscillation in microgrid operation modes. To solve this, a 3-stage energy management multi-microgrid system is proposed. The proposed system is composed of operating mode prediction by measuring the weather conditions. In islanded mode, energy management is incorporated using a two-round fuzzy-based speed (TRFS) algorithm followed by evolutionary game theory and status updating by Markov chain. The TRFS algorithm takes into account voltage, frequency, power factor, total harmonic distortion, and loss of produced power probability parameters. The parallel processing of the TRFS algorithm reduces processing time, then a Stackelberg game with a quasi-oppositional symbiotic organisms search approach is carried out for power exchange. Markov chain based future prediction of microgrid states ensures detection of microgrid operating mode along with weather changes. Simulations are developed in MATLAB Simulink, and their outcomes show better performance than previous work whose results are evaluated in terms of load and generator output at two modes, power generated at individual microgrid and exchanged power.

KEYWORDS: distributed generation, energy management, microgrid, multi-microgrid, optimization, evolutionary game theory.

Introduction

Microgrids (MGs) are becoming popular due to the increased necessity of electricity. Electricity production is affected by weather variability, and therefore an energy management system (EMS) is necessary. An EMS is efficiently designed among a single MG[1] controlling power flow through DC-DC power converters using a PI controller. Also, an EMS is presented for multiple MGs (MMGs)[2] as per the load at each building, and the electricity demand oscillates accordingly. An EMS is a functioned as a combination of distributed generation (DG) and demand response (DR) methods. MMG system is constructed with multiple individual MGs that are deployed with different renewable energy sources (RESs)[3]. In order to manage energy, a hierarchical decentralized architecture is presented. EMS in MMG design is presented based on the variations in load utilization, load demand, and power exchange between MGs. MMG architecture model is operated on grid-connected mode and islanded mode. Consumer's load and generation of DGs is supposed to impose unstable load utilization[4]. Optimization algorithms are used in order to manage the requirements of electricity in both modes. The operation of MG is performed to satisfy the economical constraint[5]. The mode of operation is based on demand, and then the battery is scheduled with the rule-based algorithm in islanded mode and receding horizon algorithm in grid-connected mode.

EMS is individually focused on any one of the operating mode[6], that must be efficiently established based on energy demand and the availability of renewable energy sources. The authors in[7] have studied the control and stability of MG considering the State of Charge (SoC) of energy storage devices inside a hybrid system, as well as state of power management for the transient response under changing conditions using a fuzzy-based PI controller[8]. Also, for MMG, grid-connected mode energy management can be achieved by using improved fuzzy logic controller[9]. Rate of change of energy at MG and SoC of the battery are the two inputs for fuzzy logic to extract fuzzy output[10].

Optimal power-sharing among distributed energy storage devices in an MG is investigated in[11], establishing a robust coordination technique between dc and ac MG sides evaluating maximum power exchanged. Management of energy grid-connected microgrid is also addressed with multi-objective optimization model[12]. An integer free optimization is used for large scale implementation with minimized mathematical computations. Based on the electricity pricing, the local power exchange is handled in a microgrid. The detection of operating mode in MMG is challenging. A hybrid islanding detection system is proposed with the development of remote detection method and passive method[13]. System stability is maintained by adjusting the error rates of voltage and current parameters. Based on these signal measurements, the islanding operation mode is either activated or switched into other stabled operation modes.

The power demand is managed by switching MG from one mode to another. A modified power control technique is proposed in order to satisfy residential load[14]. Each residence is associated with charging mode, sharing mode, and feeding mode. On estimating the power, the operation mode is switched. The management of energy is tested in both operating modes that are proposed with two stages adaptive robust optimization approach[15]. The environmental changes reflect its performance during the islanded mode. Energy management in islanded MG is addressed with the decentralized system. In a decentralized power management system, cooperation is essential for autonomous management based on their characteristic change. The challenging power control in MMG is resolved by the flexible MMG interconnection scheme[16,17]. According to the power limit, the power fluctuations rates are determined at islanded MG and grid-connected MG. Hereby power flow monitoring, load shifting, harmonic filtering, and imbalance compensation are performed. Hierarchical MMG architectures are modelled to satisfy demand and optimize the power management issues[18,19]. MIP and Stackelberg game theory are involved in solving the optimization problem. The MMG obtains information from community EMS for rescheduling. Hereby, compared to centralized MMG-EMS system models, the decentralized MMG-EMS is tedious.

In this paper, a novel centralized MMG-EMS model is proposed to predict MG operating mode, islanded MG power management, and solve an optimization problem with the Stackelberg game theory. Then the determination of a future state of MGS associates to make the accurate decision in operating mode. The novelty is a timely prediction of the operating mode of the MMG system that enables it to fluctuate into islanding and non-islanding that manages energy. The proposed centralized MMG-EMS is operated in three stages to attain better performances than the prior research works.

Overview of the Proposed Centralized MMG-EMS,

- A centralized three-stage novel energy management system (EMS) is developed in multi-microgrid (MMG) enabled to switch between grid-connected mode and islanded mode. The deployed centralized controller is responsible to manage the entire MMG-EMS. The power measurements from MGs are retrieved from smart meters (SMs).
- Firstly, the initial stage is to predict the operating mode of microgrid by monitoring the production of electricity from renewable resources. The operating mode of MGs is determined using a neural network that is executed using the environmental weather conditions around the particular MG.
- Secondly, the islanded MG undergoes power exchanges with other MG if required. TRFS algorithm, followed by a quasi-oppositional symbiotic organisms search (QOSOS) algorithm, is presented to prefer an optimal MG selection for power exchange. To minimize the number of rules in fuzzy, this work parallel runs fuzzy with two and three

parameters individually. Here the optimization problem is resolved by Stackelberg game theory.

- Thirdly, the MG detects future state from the Markov chain model, and the status is updated into the controller. The operating mode in this EMS is determined using the future status of MGs.
- The proposed MMG-EMS is designed, and the performances are evaluated in terms of server load and generator output at grid-connected mode/ islanded mode, the power generated at MGs, and power exchanged between islanded MGs.

Organization of this paper:

This paper is organized into the following structure as, Section 2 deals with previous works in MMG-EMS, Section 3 is composed of the proposed solution to overwhelm the stated problems with appropriate methodologies, Section 4 demonstrates the implementation environment along with the comparative analysis and lastly Section 5 concludes the proposed research including its future research directions.

Related works

In this section, the state-of-the-art research works in MMG-EMS are discussed. These MMG system model either operates in grid-connected mode or islanded mode. Industrial MMG was built as a hybrid under-voltage/ under-frequency islanding scheme[20]. In order to manage stability, the non-critical loads were autonomously disconnected. Loads are categorized based on their priority, which was determined from the maximum usage of energy. However, the MGs were operated at islanded mode, only when the utility grid was identified to expose with fault. The detection of fault in the utility grid by the connected microgrid was tedious. The operating mode problem was resolved by discrete particle swarm optimization (D-PSO) algorithm[21]. PSO algorithms are based on swarm behavior of animal species when searching, exploring, and exploiting resources of their environment; each particle of the PSO represents an agent with its own position, velocity, acceleration, and fitness function value related to an optimization objective function. The MMG was equipped with a three-phase/single-phase architecture model. Then the index calculation method was deployed for estimating regional capacity margin, regional continuous running time, stability margin, regional unbalance, and risk degree for predicting the islanded MMG execution. In D-PSO, the local search ability was not absolute, and hence it reflects on global results.

A model predictive control (MPC) approach was proposed in the MMG distribution system[22]. The grid-connected MG was operated in normal strategy, whereas the islanded MGs were deployed with the outage management scheme. Here the process is developed in a centralized approach that was entailed to reduce emergency states of the load. The energy storage system and state of charge (SOC) are updated in each timeslot for estimating reliability indices. The reliability was updated until stopping criteria reached; in this work, the operation mode selection was not illustrated, which is required to categorize the MG. in MMG, energy management was also attained from determining cost function for individual MG. The objective function of optimizing the net Microgrid cost was proposed by two meta-heuristics soft computing algorithms[23]. According to this work, the renewable wind farms integrated Microgrid was taken into account. The loads were categorized into two classes, and then each class was formulated as a utility function and concave function, respectively. The proposed symbiotic algorithm involves the process of mutualism, commensalism, and parasitism. The designed algorithm was explained with the conventional procedure and the procedure applied for energy was lengthier.

To compute an optimal cost in an islanded operated MG, the isolated Microgrid, a hybrid PSO (HPSO), was proposed[24]. The input parameters taken into account are micro-sources, wind, temperature, and load, which are initialized in the optimization algorithm. Finally, an optimal economic cost was determined as output for energy management. In this HPSO, the particles are randomly considered for mutation. In general, PSO is slower, and processing and hence the HPSO tends to consume larger time than the conventional PSO. A centralized, hierarchical EMS was proposed with information gap decision theory (IGDT) technique[25]. The IGDT technique was proposed with the assistance of a central controller that is present in MG. The RESs include wind turbines and photovoltaic units for formulating mathematical expressions. This hierarchical EMS deals with three controls as primary, secondary, and tertiary. The severe uncertainties depend on the varying uncertainty budget. By balancing energy in primary and secondary levels, the aim of cost minimization was attained. Nevertheless, it involves a bunch of mathematical computations.

MMGs were presented with game-theoretic non-cooperative distributed coordination control (NCDCC) scheme[26]. In this work, differential game theory (DGT) was deployed to balance the power game-theoretic agents (GTAs) in a distributed system. On obtainment of optimal global game-theoretic control coefficients, the adaptive local control of islanded MGs and grid-connected MGs was enabled. GTA plays a vital role in controlling DGs based on the power flow into MG. combination of cooperative control and non-cooperative control into MMG was tedious. The game Nash equilibrium was equipped to dynamically solve optimization problem in best-strategy-response iterative algorithm[27]. The system architecture was designed into the physical layer and management layer in which the power grid entities are in the physical layer, and local managers, MGs are in the energy management layer. Players are categorized for energy storage, load, and power sources. From the players, pay-off functions are determined, which was enabled to balance power, and then the strategy set was modeled for individual constraints. However, this work was applicable only for islanded MG.

Scheduling the utilities of MGs to minimize operational cost was developed[28]. A two-layer predictive EMS was designed based on time horizons that use two control layers-based decision making. The two layers of EMS were composed of power dispatch and energy resources. This work takes into account a degradation cost model for minimizing operational costs. According to the time period, the state of the lower layer is updated into the upper layer. Scheduling of power was enabled to reduce the operational cost of the system, where the operating mode of MG was not determined. Management of load in MGs also reflects its impact over the reduction of cost metric. An islanded MG was modeled to assist the demand side load management system. Smart load curtailment was achieved by developing a Human Activities Tracking System (HATS) with the assistance of sensors. The objective of maximizing load supply was obtained by using a fuzzy logic controller and Max-min fuzzy decision-making system[29–31]. Here significant parameters that were considered of fuzzy logic parameters include storage drain time, SOC, running load, power, and solar irradiations. The fuzzy logic controller was built up of Mamdani rules composed of a number of 100 rules. In this work, processing with 100 rules leads to higher complexity and consumes a large amount of time for decision making.

Load sharing among MGs was also concentrated over inter-unit communication using the concept of droop[32]. In his work, fuzzy logic was used by defining 49 rules from measurements of the system. The idea of limiting the number of rules has extensively minimized computations. Further, the improvements in terms of reliability and stability in an energy management system were presented by combining fuzzy logic with optimization approach[33–35]. The seeker optimization approach (SOA) was incorporated for optimizing the membership function in fuzzy that impacts on stability and reliability. Hereby, the optimization with fuzzy logic was a promising solution to improve the performance of the energy management system.

Monitoring of load at MGs enables to appropriately define the operating mode of individual MG. A wide-area monitoring system in a distributed Microgrid environment was proposed[36]. The three major processes focused on this work were fault detection, classification, and section identification. This work was operated by two sequential stages to identify the faults effectively. Both the stages use artificial neural network (ANN); in the first stage, the ANN was enabled to detect the mode of operation, and in the second stage, the fault was identified. The selection of operation mode was not based on the peculiar characteristics of MG. In[37], an adaptive ensemble filter was used for decision making regarding the operation mode. However, this classification was only based on the credibility of Extreme Machine Learning method. Grid-connected MG was involved in energy management[38,39]. A centralized MMG was handled with the deployment of a bidding strategy. This strategy involves the updating of price-quality pairs during pre-defined time intervals. Bidding was assisted for the individual's decision.

MMG model was designed especially for the purpose of cost minimization and energy management[40–42]. Target-oriented robust optimization (TORO) approach and distributive predictive control algorithm were presented to mitigate cost based on the determination of priority and future demand. From the monitored power flow characteristics, the energy management in MMG was attained.

The islanded MG was subjected to an excessive amount of load due to the demand of customers; hence, to meet all the requirements, the isolated MGs exchanges electricity. Load shedding was performed in [34] using a genetic algorithm, which was slower in performance. Then fuzzy inference system-based power quality monitoring index was proposed in[43], which models a set of 256 rules. Here a huge amount of time is consumed for decision making due to the use of a greater number of rules. In another work, cost-based priority EMS was proposed for satisfying the customers[44]. This work involved multiple computations, and it satisfies only a certain number of requirements. The excess load conditions were served by self–healing strategy, which was designed to select a MG in accordance with the economic condition[45]. The load was served with an economical generator, which considers only the cheapest where other qualified power generators were ignored. Also, multiple loads towards a particular generator cause scarcity of power generation in particular MG. The MMG defines the major problems of larger time for decision making, and demand satisfies only a limited number of customers. As discussed above, the major research works have studied the objective of energy management either in islanding mode or non-islanding mode in MMG. In general, the variation in power characteristics will certainly switch the operating mode of MMG. Hence, this paper concentrates to manage energy on both modes by detecting its operating mode initially. Management of energy satisfies customers demand without delay.

Proposed MMG-EMS

System model

The proposed MMG-EMS architecture is designed with multiple MGs. The individual MG is deployed with a SM to measure the power flow in particular MG. Let the developed MMG set up be composed of six MGs as $\{MG_1, MG_2, MG_3, MG_4, MG_5, MG_6\}$ having six corresponding SMs as $\{SM_1, SM_2, SM_3, SM_4, SM_5, SM_6\}$. The system model is depicted in Figure 1 with the utility grid (UG) and MGs.

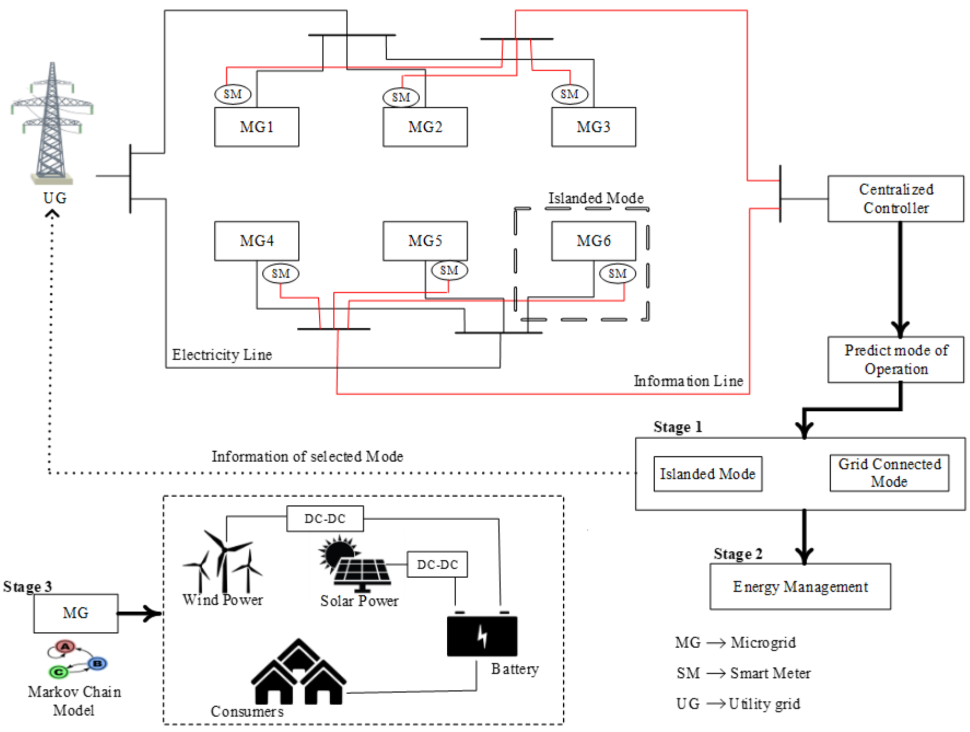

Figure 1. Proposed MMG-EMS Model.

A MG consists of RES as wind and solar with battery storage. Consumers demand is satisfied by islanded mode or grid-connected mode. Each MG is associated with an information line from SM and electricity line towards the UG. The information line from SMs approaches the centralized controller. The proposed MMG is executed as a three-stage novel EMS. The initial stage is to predict operating mode of MG followed by management of energy in islanded mode, and lastly, the MG status is updated for accurate prediction of operation mode using future states. SMs are the special entities that are enabled to monitor and report exact measurements of the electricity flow. Using these values, energy management is attained. The variations in electricity utilization and production on each MG are gathered from the central controller for decision making. As per the decision from the central controller, the MGs are operated. On the other hand, MGs status is monitored for future prediction of the MG status. The accurate determination of operation mode ensures to manage energy without any faultless execution. The novel three-stage MMG-EMS is proposed to achieve the objective of energy management by appropriate mode selection and power exchange.

Stage 1 – Operation mode prediction

Operation mode in MMG is classified into two as: (i) Grid-connected mode and (ii) Islanded mode. An islanded operating mode MG is supposed to have some self-electrical sources which are used to serve consumers demand. In this mode, the generation of electricity is not the same for all the time due to the use of renewable resources. Renewable resources as wind and solar are environmentally dependent, which is not able to produce electricity 24/7. The grid-connected operation mode is not similar to islanded mode since it automatically generates the same amount of electricity for all time without any lag. Here the weather condition plays a vital role in power generation on MGs. In order to predict the mode exactly, a back propagation neural network (NN) is involved with the consideration of weather conditions around the MG. Backpropagation NN algorithms are based on supervised learning, in which inputs and desired outputs are provided to the NN for the training process. In backpropagation algorithms, the error between output and the desired output is sent back from the output layer to hidden layers to adjust neurons weights.

In this stage, the weather conditions of individual MG are extracted, and they are classified into operation mode decision. The renewable resources used here are wind and solar, so the corresponding weather changes measured are wind speed and light intensity. In general, the light intensity is defined as the measurement of monochromatic radiation of frequency. Let L_I be the light intensity estimated at time t. This work is assumed to use light intensity values that are extracted from summer seasons since different seasons also reflect on solar. Then wind speed is taken into account for the renewable energy resource of a wind turbine. Conventionally, the wind speed is different based on the height of the turbine hub. The density of air is varied in accordance with the elevation of the wind turbine. Let W_S be the wind speed at time T. By taking into account environmental constraints into NN, for determination of operating mode.

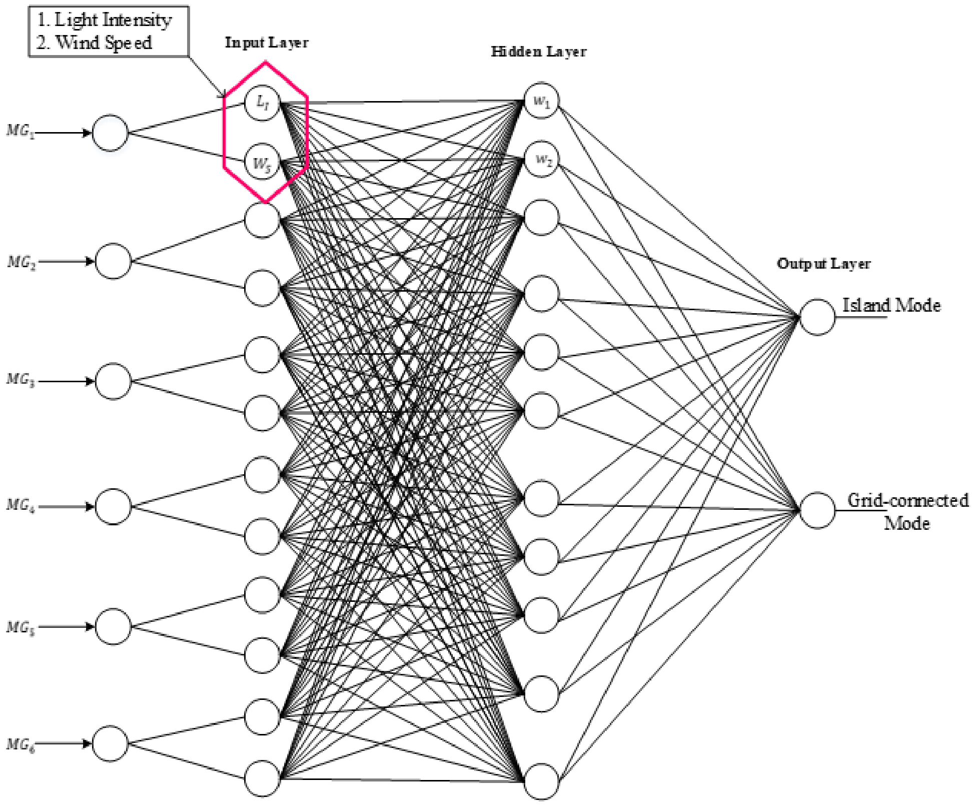

Figure 2. NN design.

NN is a machine learning system that is inspired by the human brain neuron's operations. The structure of NN is composed of layers of input, hidden and output neurons, see Figure 2, i.e., based on the backpropagation algorithm. The neurons in the input layer are connected with hidden layer neurons, and all the neurons in the hidden layer are connected with output layer neurons. The proposed NN works well in solving complex decision-making problems. The consecutive layers of neurons are connected via links, let i and j be two neurons whose weight is defined as $w(i,j)$. The input entering the neurons is entailed to determined the weighted sum from propagation functions, and then the input is transformed as an input for the next layer by using an activation function. Hereby the input from MG_1 is given as net_{MG_1}, consider $I = \{i_1, i_2, i_3, \dots, i_n\}$. With this, propagation function is modeled as,

$$net_{MG_1} = F_{Pro}(o_{i1}, o_{i2}, \dots, o_{in}, w_{i1,j}, w_{i2,j}, \dots, w_{in,j}) \quad (1)$$

The propagation function $F_{Pro}$is composed of weighted values and outputs from other layers as $(o_{i1}, o_{i2}, \dots, o_{in})$. The weighted sum is predicted by multiplying individual neuron with the weight $w_{i,j}$. The activation function is used to activate the neurons only when it beats the threshold value. Let Θ_i be the threshold of i^{th} neuron, hereby the activation function is given as,

$$A_i(t) = F_{act}(net_i(t), A_i(t-1), \Theta_i) \quad (2)$$

F_{act} denote the activation function, $net_i(t)$ is the network input, $A_i(t-1)$ represents the previous activation state which is converted into $A_i(t)$ that is a new activation state. The neurons present in the NN are enabled to fine-tune the stability of the connection, in order to increase output accuracy. Based on the training samples that are composed of the varying values of L_I and W_S the neural network makes the decision regarding the operating mode. On the other hand, the estimation of future status in stage 3 ensures to predict accurate operation selection. The significant constraints of RES in MG are taken into account for identifying their operation mode since the MGs are distributed in the environment. Also, their electricity production depends on the natural resources, and hence light intensity and wind speed are taken into consideration for predicting their operation mode. If the external weather condition is poor, it tends to reduce production, which reflects with dissatisfaction of user demands. In this case, the MGs are operated in grid-connected mode until the production by RES reaches a particular range. Then the islanded MG is carried over to the processing of stage 2.

Stage 2 – Islanded mode

In this stage, the islanded MG effectively manages energy with power exchange. Novel TRFS algorithm, followed by game theory, is proposed in this stage for predicting optimal MG that is applicable to exchange power with other needy MG. Stackelberg game with a quasi-oppositional symbiotic organisms search approach is presented in this work. The designed TRFS algorithm involves parallel processing fuzzy in order to enrich the time. The five major constraints that are used in this TRFS algorithm are voltage, frequency, power factor, total harmonic distortion, and loss of produced power probability. The power exchanging decision is also made by a centralized controller, which updates the SM measurements from each grid. Information from SMs plays a vital role in decision making so that the MGs retain in the islanded mode for a longer time period.

Voltage and Frequency – Voltage and frequency are the typical metrics that are measured as system parameters. According to the time, the voltage U and frequency f_q are periodically measured in islanded mode operating MGs.

Power factor – Power factor (PF) of islanded MG is determined from the power available in a wind turbine, solar, and battery. Let the power factor of MG_1 be formulated as

$$PF(MG_1)_t = P_{wt}(t) + P_{sr}(t) + P_{br}(t) + P_L(\mathrm{t}) \quad (3)$$

The summation of $P_{wt}(t)$ wind turbine power, $P_{sr}(t)$ solar power, $P_{br}(t)$ battery power and $P_L(t)$ and load power factor at time t is predicted as $PF(MG_1)_t$ and similarly for individual MG. Assume the wind speed as 14 - 15 m/s and the rated power reached nearly 500 watts having 1.8m of blade diameter. Solar photovoltaic power is generated from the higher frequency radiation of the sun. The title angle and number of panels effects of power production.

Total harmonic distortion – Harmonic distortion is a significant constraint that is projected due to nonlinear loads. The total harmonic distortion (THD) is defined mathematically as the ratio of root mean square of harmonic magnitude and its frequency. This constraint profoundly impacts on MG operating in islanded mode.

Loss of produced power probability – This loss of produced power probability (LP) defines the curtailed power expressed from unutilized energy and energy produced from renewable sources of particular MG. Hereby the mathematical estimation of LP is given as,

$$LP(MG_1)_t = \sum_{t=1}^{Max} (P_{us}(t) + P_{RES}(t)) \tag{4}$$

The LP for MG_1at time t is depicted in the above equation with $P_{us}(t)$, $P_{RES}(t)$ as unutilized power and renewable energy power at time t respectively. For each MG, till the maximum time, the LP is determined periodically.

The estimated five parameters are enabled to satisfy the following condition,

$$U_{min}(t) \le U(MG_x)_t \le U_{max}(t), x \in \{1, ..6\} \tag{5}$$

$$fq_{min}(t) \le fq(MG_x)_t \le V_{max}(t), x \in \{1, ..6\} \tag{6}$$

$$PF_{min}(t) \le PF(MG_x)_t \le PF_{max}(t), x \in \{1, ..6\} \tag{7}$$

$$THD_{min}(t) \le THD(MG_x)_t \le THD_{max}(t), x \in \{1, ..6\} \tag{8}$$

$$LP_{min}(t) \le LP(MG_x)_t \le LP_{max}(t), x \in \{1, ..6\} \tag{9}$$

The parallel processing fuzzy logic system modeled as TRFS, which equips two interference engines for predicting higher and lower valued MGs. From this fuzzy result, the lower output values are elimination, and higher values are taken into consideration for optimal selection of MG.

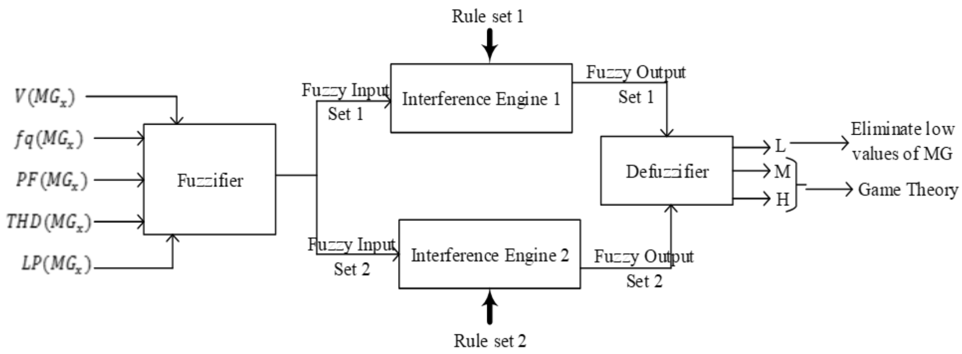

Figure 3. TRFS algorithm

The fuzzy logic system is composed of three major components as fuzzifier, interference engine, and defuzzifier. The proposed TRFS algorithm is illustrated in Figure 3, which deals with two interference engines, and each differs in their rule set. The first three parameters are given in interference engine 1, and the last two parameters are taken into account on interference engine 2. The rule set is deployed with "If….Then" rules based on the Takagi-Sugeno fuzzy model. Here the interference engine one is fed with eight rules and engine two with four rules, however here, the mathematical computation time of the last two parameters equalizes the processing time at these interference engines.

Table 1. Fuzzy rules for TRFS algorithm.

Rule Number	Interference Engine 1			Out 1	Interference Engine 2		Out 2
	U	f_q	PF		THD	LP	
Rule 1	L	L	L	L	L	L	L
Rule 2	L	L	H	L	L	H	M
Rule 3	L	H	L	L	H	L	M
Rule 4	L	H	H	M	H	H	H
Rule 5	H	L	L	L	-	-	-
Rule 6	H	L	H	M	-	-	-
Rule 7	H	H	L	M	-	-	-
Rule 8	H	H	H	H	-	-	-

The value of U is measured to be high and low if it ranges between [8-14] and [15-25], respectively. Similarly, the frequency [49-51] is high and [47-49] is poor, the PF with [0.7-1] is high and [0.4-0.6] is low, and THD is high if it is [0-10] and poor [≥10], then LP which defines the reliability of the microgrid ranges [0-1] where [0.3-1] is low and [≤0.4] is high. Table 1 depicts the fuzzy rules that are fed into the individual interference engine and their corresponding output. In the table 'L, M, H' represents low, medium, and high values based on the measurements. Hereby, the low output value is eliminated, and the MG with medium and high are taken into account for identifying optimal MG to exchange power. The high and medium output values are fed into the evolutionary game theory of the Stackelberg game with quasi-oppositional symbiotic theory. In a Stackelberg game, each player, or agent, is selfish and aims to maximize utility, there are leaders and followers. Leaders are the players with the best response, that is, best utility; followers adapt their strategies accordingly to best leader strategies to maximize utility. In this work, each MG is considered to be a player. To exchange the required amount of power between players, a Stackelberg game is proposed and combined with the quasi-oppositional symbiotic organism search to find the best power exchange for the MMG environment. The Stackelberg game initializes the number of players that is high output MGs from the TRFS algorithm. The pay-off function in Stackelberg game theory is given based on three constraints as demanding consumers, fuzzy output, and current load at individual MG. The proposed three-stage Stackelberg game enabled the MG to act as power storage and utility. Each MG's payoff is maximized by regulating the amount of power and required consumer's demand. As per the proposed design, MG is equipped with RES of wind and solar for power generation to satisfy consumers and also shares power with other MG if requested. The steps are as follows,

Step 1: Initialize a number of players, i.e., the number of islanded MG in the environment. Consider fuzzy output, demanding consumers, and load at MG. The load depends on the power utilization of consumers connected with each MG.

Step 2: Based on these constraints, the ecosystem matrix is defined as,

$$X_i = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ \cdots \\ X_n \end{bmatrix} \tag{10}$$

Let X_i be the total number of islanded MG with n number of players.

Step 3: In this step, mutualism is performed using i^{th} MG in the ecosystem and j^{th} MG which is randomly chosen from the MG environment. The mutual vector is determined as,

$$MV = \frac{X_i + X_j}{2} \tag{11}$$

This MV mutual vector depicts the mutual relationship between MG i and j, which includes their operating mode and previous power exchanges. Then the payoff function considers fuzzy output, consumer demand, and load as its primary constraints. The payoff function defines utility which is expressed as,

$$u_i = F_i, i \in n \tag{12}$$

The term u_i is the utility function for i^{th} MG and similarly for n MGs that area operated in islanded mode. Hereby, the payoff function F_i is defined as

$$F_i \in \{F_{f(i)}, F_{D(i)}, F_{L(i)}\} \tag{13}$$

$F_{f(i)}, F_{D(i)}$ are the fuzzy output [0-1] and the demanding number of customers, respectively. The $F_{L(i)}$ is the load at i^{th} MG whose load is formulated as

$$L_i = (P_R + P_O) \tag{14}$$

From this expression, P_R denotes a refrigerator load and P_O is the other load that includes light, fan, television, and any other home appliances. In this work, we assume the consumers as residencies, and hence the residential sector load is computed. Hence the strategy of each MG is evaluated with the maximum and minimum set.

Step 4: In the commensalism phase, the requirement matching MGs in the ecosystem is generated on a random basis. Then, a new solution X_1 is determined with the estimation of fitness, and if the best fitness is attained, it is replaced else, the previous value is maintained. The new fitness value is given as,

$$X_{i(new)} = X_i + rand(-1,1) * (X_{best} - X_j) \tag{15}$$

The X_{best} is the current best MG having a higher pay-off function in the MMG environment.

Step 5: Process with step 2, if the current MG is not the last islanded MG. Find an optimal MG for exchanging power that ensures to satisfy the consumer demand.

Step 6: Execute the procedure until the termination condition is reached, process the loop from step 2 to the end.

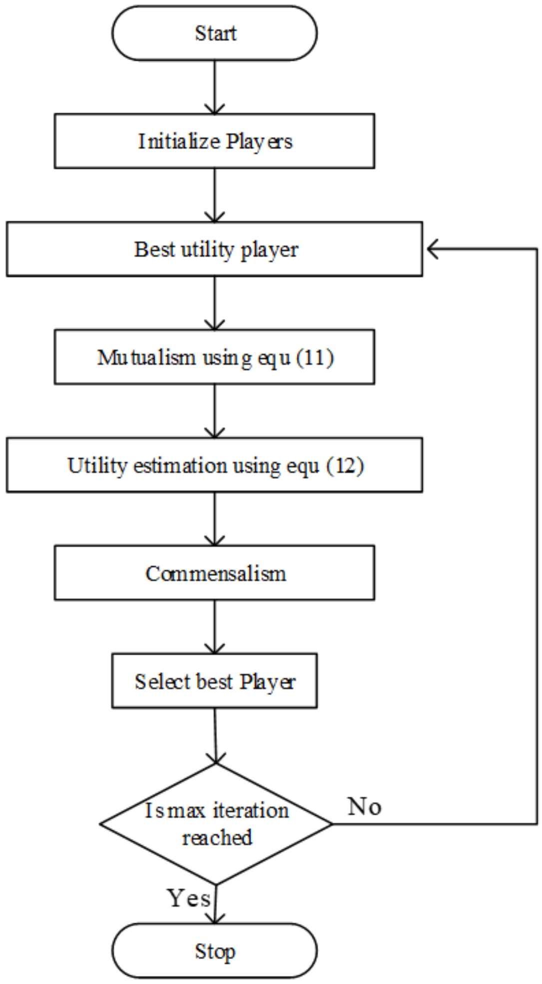

Figure 4. Flow chart of Stackelberg game theory with quasi-oppositional symbiotic organisms search algorithm.

The Figure 4 demonstrates the workflow of the proposed Stackelberg game theory with a quasi-oppositional symbiotic organisms search algorithm, which is presented to select optimal MG for power exchange. Considering the significant parameters of MG, it ensures to prefer appropriate MG for power exchange. Here Stackelberg game is initialized with the number of players and utility function for each player, which is determined along with the quasi-oppositional symbiotic algorithm, and the best player is estimated. The MG parameters are estimated in the payoff function, which is the key to select the best MG.

Stage 3 – Future status determination

In this stage, the future state of individual MG is predicted based on the previous state. Markov chain model is deployed for identifying whether the future state of the MG is grid-connected or islanded. Let the status of MG be $\{MG_i, MG_g\}$ that represents MG in islanded and grid-connected mode. The designed Markov model is operated in discrete-time, which is equipped to update the status timely. The three sequences of the proposed Markov model are modeling possible states, determination of possible states, and prediction of transition probability.

Determination of future state requires past state for accurate identification, Assume the discrete-time $t = 1,2,3, \dots, \infty$ whose states are updated periodically. Bernoulli p distribution is modeled for request arrivals over random variables. The probability of transmission from one state to another is given as,

$$p_{ab} = P_r\left(X_{(f+1)} = b | X_f = a\right), \qquad \forall\, f = 0,1,2 \dots. \tag{16}$$

$$p_{ab} = P_r\left(X_{(f+1)} = b | X_f = a, X_{(f-1)} = a-1, X_{(f-2)} = a-2 \dots \dots X_0\right)$$
$$\forall\, f \geq 0, a, b, a-1 \dots \in S \tag{17}$$

The probability of MG is represented as p_{ab} whose states are X_f. Here S defines the sample states, and $f+1$ is the number of transitions probability that are crossed before reaching state b. the possible transition state is expressed as,

$$P_{r,oo} = p(1-p) \tag{18}$$

p is the arrival data, let the initial state be a and its transmission probability at time $t = 0$ is defined as,

$$r_{ab,n} = P_r(X_f = b | X_0 = a) \tag{19}$$

Let X_f be the final states of the MG, which is reached after transitions in the past time. Hereby the initial state X_0 begins from the following,

$$r_{ab,0} = \begin{Bmatrix} 1; & if\ a = b \\ 0; & otherwise \end{Bmatrix} \tag{20}$$

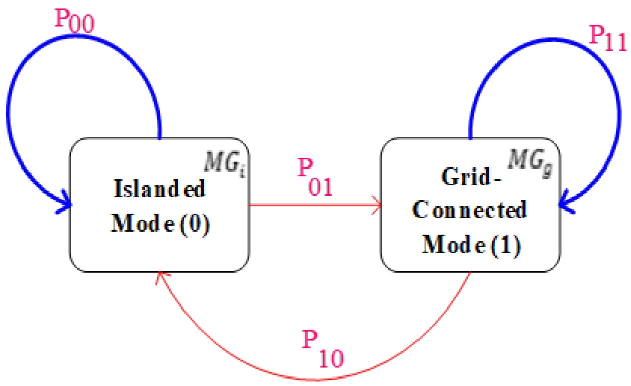

Figure 5. Markov Chain Model.

Therefore, the total number of probabilities is formulated after completion of the first state, that is expressed as follows,

$$r_{ab,f} = \sum_{a=1}^{m} P_{a1} r_{ib}(f-1), \forall\, a, b \in S \tag{21}$$

From the random initialization of the initial state as $X_0 = a$, determines the final state after $r_{ab}(f)$ transitions. The Figure 5 depicts the two different states of MG that are participating in the proposed MMG-EMS design. Let a and b the two states involved in the MMG system model and the four probability of state transitions are P_{00}, P_{01}, P_{10} and P_{11}. Updation of this individual MG's future state associates with an accurate prediction of the next operation state along with the external environmental characteristics.

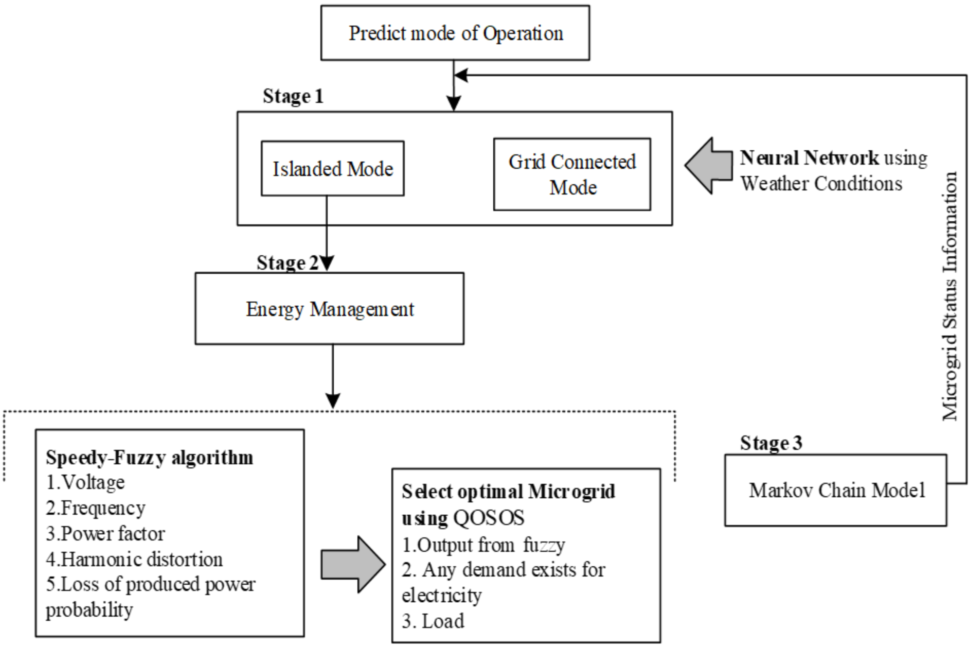

Figure 6. Workflow of Three-Stage MMG-EMS.

The Figure 6 demonstrates the overall workflow of the proposed three-stage MMG-EMS by representing the stages handled and their corresponding algorithms used. The main objective of this proposed MMG-EMS is to select appropriate MG operating mode, which enabled to satisfy user demands and reduce fluctuation in changing operating mode. The proposed mode selection and energy management are efficient in achieving better performance results.

Experimental results

In this section, the proposed MMG-EMS performance is validated by developing it with appropriate programming. This section is categorized into two as a simulation environment and comparative results.

Simulation environment

The proposed MMG-EMS model is investigated using MATLAB Simulink. This tool is a graphical programming environment that is specialized to design dynamic systems of RES. MATLAB R2017b suits the development of MMG-EMS with three-stage processing of mode identification, energy management, and future state prediction. MatlabR2017b is installed on Windows operating system.

Table 2 Simulation setup.

Parameter		Specification
Number of Microgrid		6
Number of windmills		6
Number of PV		5
Mode of Operation		Islanded / Grid-connected
Renewable Energy Capacity	PV	60kW
	Wind	60kW
	Battery	150kW
External grid		200kW
Simulation time		200s

The Table 2 details the proposed MMG-EMS specifications that are considered in account of our design. These constraints are not limited to this; the modeled MMG-EMS is composed of six microgrids, and each was varying in their load. According to their production, their operational mode is decided by the controller. Based on these specifications, three-stage measurements are performed by mode prediction, energy management, and power exchanges. Energy management in islanded mode is concentrated.

Table 3 TRFS Specification.

Field		Value
Fuzzy logic controller		Struct
Fuzzy type		Mamdani
Number of inputs	Engine 1	3
	Engine 2	2
Number of Output		3
Number of rules	Engine 1	8
	Engine 2	4

The accurate predictions of operating mode form weather changes along with the predicted future state ensure energy management. The involvement of QOSOS with Stackelberg game theory is presented for identifying the appropriate MG for power exchange in case of demand. In this work, initially, the low rated MGs are eliminated by rule-based TRFS algorithm whose specifications are shown in Table 3. Only the high rated MGs are carried over into game theory by which a strategy set is constructed, and optimal MG is preferred for power exchanged, which can satisfy the demand. Here the use of game theory associates to support large scale MMG-EMS environment.

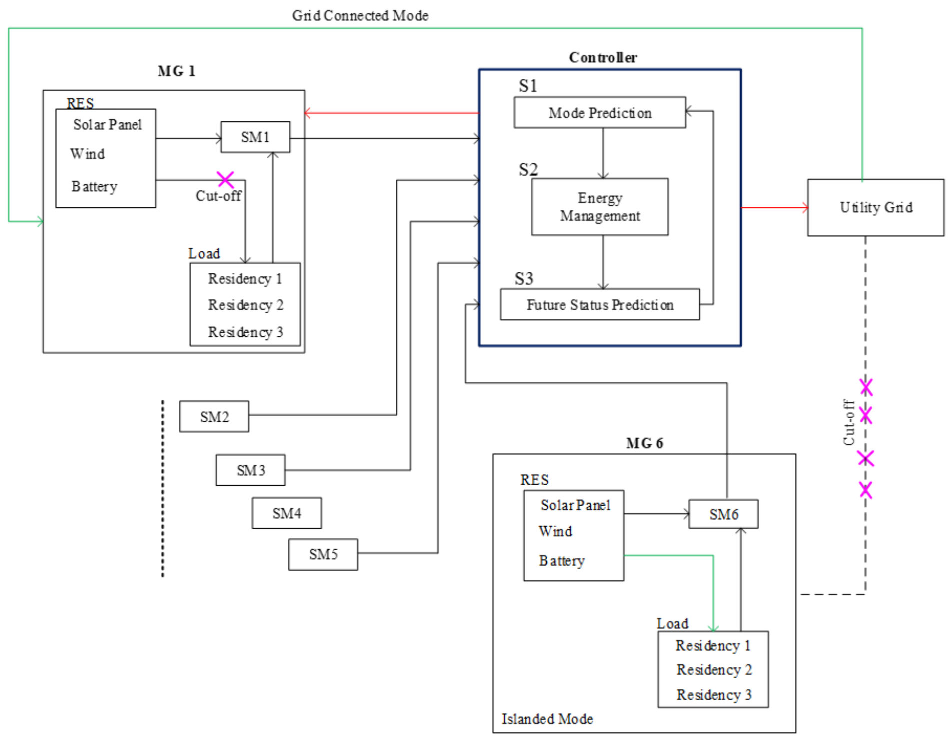

Figure 7. Pipeline Structure of Proposed MMG-EMS.

The proposed MMG-EMS is developed in MATLAB Simulink, and its general pipeline structure is depicted in Figure 7. The centralized controller is responsible for performing the three stages (S1, S2, and S3). The stages of controller processing are illustrated in section 4.2, section 4.3, and section 4.4. Overall their performances are evaluated by comparing with previous work in the forthcoming section.

Comparative analysis

MMG-EMS is compared with previous priority-based MG EMG in[46]. In the previous work, the cost was the only parameter evaluated to satisfy user demand. The objective of this work is to manage energy in MMG based on the load at MGs, and hence this work is preferred for comparison. According to this work, the priorities for loads are pre-defined by the user's opinions. In order to exchange power, the cost constraint is taken into account; if not satisfied, they move on to the utility grid. Due to its work procedure of prior prediction of load for energy management, this work is significantly preferred for comparison. In this work, the significant parameters that are compared are load server, the power generated, and power exchanged.

Load served

The main aim of designing the MMG system is to serve loads promptly without any scarcity. For this purpose, the designed MGs are subjected to be operated on two different modes as islanded and grid-connected. The islanded MGs generate power by own RES, here residential loads are considered on the individual grid. Hereby, serving the load demands play a major role in evaluating the performances.

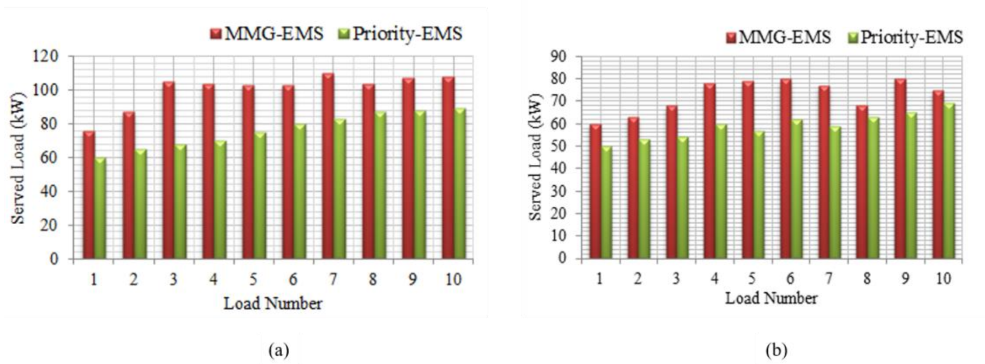

Figure 8. Served Load (a) Grid Connected Mode and (b) Islanded Mode.

As per the increase in the number of loads, the requirement for power is also larger on the other hand. However, if the load is higher, then the amount of load served is essential to be higher. Figure 8 (a) and (b) depicts the evaluated load functioned with the corresponding load in terms of their operating mode. The comparison shows that the priority-EMS was able to serve a lesser number of loads when compared to proposed MMG-EMS in both the operating modes. However, there is a drop in served load; it is not poor than the previous work. Hereby, the grid-connected mode is capable of serving a larger number of loads than the islanded mode; anyhow, the islanded mode can also exchange power in case of scarcity. Approximately 5-10% of the load served is higher than Priority-EMS. This priority-based EMS was not able to predict accurate operating mode due to the provisioning of priority, and also, the power exchange was based on cost constraint, and hence the proposed MMG-EMS is better than this work.

Power generated.

MMG system is developed for the effective utilization of generated power. The generation of power in individual MG is differed due to the varying weather conditions and the availability of installed RES. However, the wind turbine and photovoltaic (PV) solar are deployed; they depend entirely on environmental factors. The power generation in MG is based on renewable energy, and also increase in customer demand will also reflect with an insufficient amount of power.

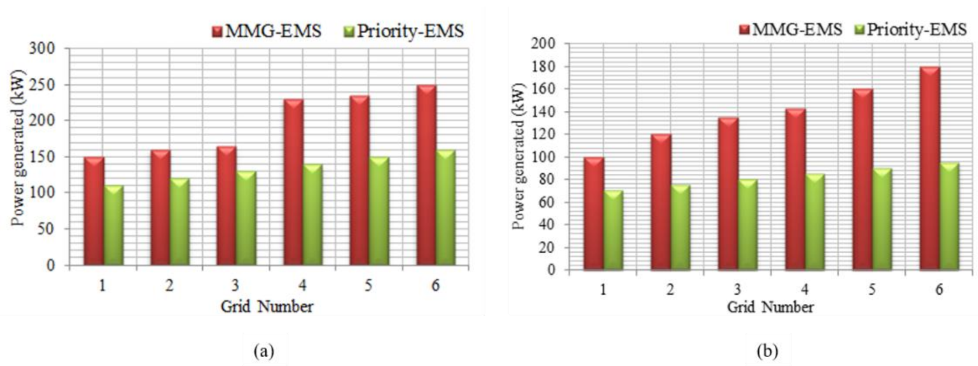

Figure 9. Power generated (a) Grid Connected Mode and (b) Islanded Mode

Power generation is continuously performed in both the operating mode. The Figure 9 (a) and (b) demonstrates the power generation in MMG-EMS and priority-EMS under grid-connected mode and islanded mode. In both works, the power generation in grid-connected mode is higher than the islanded mode due to the environment dependable renewable energies. According to increase in number of grid, the power generation is also gradually increased due to the involvement of more number of energy sources. Nearly 5-10% of the power generated is larger in the proposed MMG-EMS system whereas, 10-15% higher in islanded mode. Energy management in islanded mode by optimal MG selection achieves higher power generation among the MG, while the previous priority-EMS exchanges power by estimating cost function. Cost-based priority was not affordable, and selecting mode without weather constraints impacts on power generation. On the whole, an increase in power generation ensures to assist the entire customer load without any lay. Appropriate mode selection of optimal MG preference enabled to attain larger power in the designed MMG-EMS environment.

Power exchange

Power exchange is a significant process handled in the MMG system. In case of power scarcity in an individual MG, then the operation mode will be islanded, by which the MG exchanges power between MGs. Power exchanges are carried over in terms of watts. Table 4 illustrates the amount of power exchanged between the numbers of MGs.

Table 4. Comparison of Power Exchange.

# of MGs	MMG-EMS	Priority-EMS
1	100W	50W
2	150W	75W
3	240W	120W

The exchange of power will be higher only when the MG is optimally selected. Comparatively, the power exchange in MMG-EMS is larger than the priority-EMS, whose power exchange is 50% lesser. While exchanged power based on the cost function, it satisfies only to a particular constraint. Hereby the proposed system with accurate mode prediction and optimal MG selection enables to attain the required amount of power exchange.

Hereby the proposed MMG-EMS system is equipped with appropriate operating mode selection followed by optimal MG selection and, lastly, future state prediction.

Conclusion

In this paper, an MMG is designed with a centralized novel three-stage EMS. The three stages are operating mode selection, manage energy in islanded mode, and predict the future status of MGs. Each stage encompasses algorithms as neural network, TRFS, QOSOS with game theory, and Markov chain. Accurate determination of operating mode enables to manage customer's load and minimize fluctuations in switching operating mode as well as manage energy. The consideration of weather conditions is highly reflected in the production of electricity among the RES. Hence, the prediction of operating mode is required to be appropriate. Once the mode is determined, then the MG is insisted to be operated on that particular mode. If it is in state of power scarcity, power exchanging is performed without changing its operating mode. For exchanging power, an optimal MG is chosen using TRFS followed QOSOS with game theory. The MGs with low power generation are predicted by TRFS and ignored in this step, and later the optimal MG is chosen from a game theory based QOSOS. By the optimal selection of MG, it enables to reduce a frequent number of modes switching. In case if the MGs were not able to satisfy the demand along with poor weather conditions, then the MG will be switched to the grid-connected mode by the controller. Markov chain based future prediction associates to predict accurate operating mode of MGs.

In the future, this work is planned to be extended in decisions making as well as a concentrate of security aspects in the information line.

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List of Symbols and Abbreviations:

ANN	artificial neural network
DG	distributed generation
D-PSO	discrete particle swarm optimization
DR	demand response
EMS	energy management system
f_q	frequency
GTA	game theoretic agent
HATS	Human Activities Tracking System
H-PSO	hybrid particle swarm optimization
IGDT	information gap decision theory
LP	loss of produced power probability
MG	microgrid
MMG	multi-migrogrid
MPC	model predictive control
NCDCC	non-cooperative distributed coordination control
PF	power factor
QOSOS	quasi-oppositional symbiotic organisms search
RES	renewable energy sources
SM	smart meter
SOS	state of charge
THD	total harmonic distortion
TORO	Target-oriented robust optimization
TRFS	two round fuzzy-based speed

U	voltage
UG	utility grid

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Conflict of Interest Statement

The authors listed in this paper declare no conflicts of interest.

Capítulo 3.

Discusión, conclusiones y trabajo futuro

3.1 Discusión y conclusiones

La discusión y conclusiones del presente trabajo de investigación se dividen en dos categorías, las discusiones y conclusiones relacionadas con la mejora del control primario de las microrredes a través de la implementación de algoritmos de optimización en la mejora de los controladores, y las discusiones y conclusiones relacionadas al control secundario y terciario, donde se implementaron modelos para la gestión óptima de la energía y el intercambio de potencia entre las diferentes fuentes de una microrred, así como en un entorno de dos o más microrredes. A continuación, se detallan las discusiones y conclusiones.

Sobre el control primario en este proyecto de investigación se trabajó en el modelo de los convertidores de potencia y una estrategia de sintonización de sus controladores PID por medio de algoritmos bio-inspirados. Se emplearon los algoritmos de manada de lobos (GWO, Grey Wolf Optimizer), enjambre de partículas (PSO, Particle Swarm Optimization) y genético (GA, Genetic Algorithm) comparándose con métodos clásicos de sintonización como lo son el método de las oscilaciones sostenidas de Ziegler-Nichols para evaluar el desempeño de los controladores PID propuestos bajo condiciones de voltaje de entrada variable y carga cambiante. Los convertidores de potencia se modelaron matemáticamente mediante sus ecuaciones de espacio de estado y circuito eléctrico. La implementación de los modelos y su simulación se realizó mediante el programa de Matlab/Simulink. Los resultados obtenidos se evaluaron en términos del RMSE entre el valor de salida de voltaje consigna y el valor de voltaje obtenido para diferentes configuraciones y diferentes métodos de optimización.

De acuerdo con los resultados mostrados en las publicaciones del Capítulo 2 del presente trabajo, en general, los controladores PID sintonizados mediante algoritmos bio-inspirados mostraron un desempeño mejor que aquellos sintonizados por métodos clásicos, con la ventaja extra de que el algoritmo bio-inspirado es capaz de buscar soluciones más rápidas y fuera del espacio tradicional de los métodos clásicos. En concreto, hablando de controladores de convertidores de potencia, el algoritmo GWO tuvo un mejor desempeño con un RMSE un 50.89% menor que el mismo controlador sintonizado por el PSO y 44.70% menor que su equivalente con algoritmos GA, y un 63% menor que el obtenido por el método de las oscilaciones sostenidas de Ziegler-Nichols. Se observó que los algoritmos de PSO y el GA son susceptibles de quedarse atrapados en óptimos locales, mientras que el GWO al imitar el mecanismo de cacería de los lobos es capaz de encontrar una mejor solución global. Adicionalmente a esto, se observó que el GWO tiene ventajas computacionales respecto al PSO y GA puesto que requiere menos parámetros de configuración previos a la optimización y menores tiempos para la convergencia al óptimo, hasta un 35% más rápido según el algoritmo. La Tabla 2 resume los principales resultados y hallazgos de esta investigación sobre algoritmos bio-inspirados aplicados al control primario en una microrred eléctrica.

Tabla 2 Resumen de hallazgos en la aplicación de algoritmos bio-inspirados en el control primario en microrredes eléctricas.

Control primario	**Algoritmos de optimización bio-inspirados**
Modelo de los convertidores de potencia	Algoritmos de manada de lobos (GWO), enjambre de partículas (PSO) y genético (GA)
Desempeño de los controladores PID propuestos	Mejor desempeño que los sintonizados por métodos clásicos
Ventajas de los algoritmos bio-inspirados	Capacidad para buscar soluciones más rápidas y fuera del espacio tradicional de los métodos clásicos, capacidad para encontrar soluciones globales y requerir menos parámetros de configuración previos y menores tiempos para la convergencia al óptimo
Resultados de los algoritmos de optimización	GWO mostró el mejor desempeño con un RMSE un 50.89% menor que el mismo controlador sintonizado por el PSO y 44.70% menor que su equivalente con algoritmos GA, y un 63% menor que el obtenido por el método de las oscilaciones sostenidas de Ziegler-Nichols

Fuente: Elaboración propia.

Sobre el trabajo en control secundario y terciario de la microrred en este trabajo de investigación se diseñó un nuevo modelo en tres etapas de un sistema de gestión de la energía para un entorno de varias microrredes. En este punto, no solamente fue importante trabajar sobre la mejora de la calidad de la energía dentro de la microrred, cosa que fue lograda mediante el control primario, sino que también se establecieron criterios y estrategias para implemente un Sistema de Gestión de la Energía (SGE) capaz de (i) seleccionar el modo de operación de la microrred, (ii) gestionar el flujo de energía dentro y fuera de la microrred y (iii) predecir estados y requerimientos futuros de la microrred. Para cada una de las anteriores tareas del SGE se implementaron y combinaron diversas técnicas metaheurísticas: redes neuronales artificiales, sistemas de lógica difusa y algoritmos de optimización bio-inspirados. El poder determinar de manera adecuada el mejor modo de operación de la microrred permite que el usuario cubra su demanda de energía, al mismo tiempo que se aumenta la resiliencia del sistema al habilitar un intercambio energía entre las diferentes fuentes dentro de la microrred e incluso entre otras microrredes, según la metodología mostrada en los artículos científicos de la previa sección. El modelo propuesto de SGE implementando técnicas y algoritmos metaheurísticos bio-inspirados mostró ser eficiente, y tener ventajas sobre las técnicas comparadas, como por ejemplo, la posibilidad de encontrar soluciones fuera del espacio de soluciones típicos que los algoritmos clásicos abarcan, poder ser implementados de manera automática sin necesidad de un exhaustivo análisis matemático del sistema, entre otras, según se muestra de manera detallada en cada una de las publicaciones relacionadas del Capítulo 2. En el caso de que las microrredes del entorno multi-microrred no puedan proveer de energía debido a pobres condiciones ambientales entonces las microrredes entrarán por medio de una orden de un controlador central que alberga al SEG a un modo operación en interconexión con la red eléctrica para proveer de energía a sus usuarios y así cubrir la demanda de energía. En la Tabla 3 se detallan algunos de las principales características del SGE desarrollado para el control secundario y terciario en una microrred.

Tabla 3 Principales características del SGE desarrollado.

Control secundario y terciario	**Técnicas metaheurísticas**
Modelo en tres etapas de un sistema de gestión de la energía	Redes neuronales artificiales, sistemas de lógica difusa y algoritmos de optimización bio-inspirados
Funciones del Sistema de Gestión de la Energía	Seleccionar el modo de operación de la microrred, gestionar el flujo de energía dentro y fuera de la microrred, predecir estados y requerimientos futuros de la microrred
Ventajas del modelo propuesto de SGE	Eficiencia y capacidad para encontrar soluciones fuera del espacio de soluciones típicos que los algoritmos clásicos abarcan, posibilidad de ser implementado de manera automática sin necesidad de un exhaustivo análisis matemático del sistema
Modo de interconexión con la red eléctrica	Si las microrredes no pueden proveer de energía debido a pobres condiciones ambientales

Fuente: Elaboración propia.

La anterior Tabla 3 muestra un resumen de las características del SGE presentado en esta investigación para una microrred, el cual es capaz de seleccionar el modo de operación, gestionar el flujo de energía y predecir estados y requerimientos futuros. Las técnicas implementadas se detallan en las respectivas publicaciones del Capítulo 2 de esta investigación. Los resultados indican que la combinación de estas técnicas metaheurísticas en el modelo propuesto de SGE permitió encontrar soluciones más eficientes y fuera del espacio de soluciones típicos que los algoritmos clásicos abarcan, lo que resulta en una mayor resiliencia del sistema y una mejor gestión de la energía dentro de la microrred.

Sobre los hallazgos particulares en cada una de las publicaciones, a continuación, se presenta un breve resumen y discusión.

Publicación 1.- Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller.

En esta publicación se presentó un estudio comparativo del desempeño de tres algoritmos metaheurísticos para la optimización de un controlador PID para un convertidor boost de CC-CC. El trabajo muestra cómo la implementación de los algoritmos PSO, GA y GWO permitió encontrar valores óptimos para el controlador a través de la simulación del sistema en MATLAB/Simulink. Los resultados obtenidos permitieron determinar cuál de los tres algoritmos proporcionó el mejor desempeño para la aplicación específica del convertidor boost y cómo cada uno de ellos puede ser más o menos susceptible a caer en soluciones óptimas locales o globales. Este trabajo puede resultar de gran interés para el diseño y optimización de controladores para convertidores de potencia.

Tabla 4 Comparación del desempeño de los algoritmos PSO, GA y GWO en la sintonización de un controlador PID para un convertidor Boost DC-DC.

Algoritmo	**RMSE (%)**	**Diferencia con GWO (%)**
PSO	20.43	50.89%
GA	18.29	44.70%
GWO	10.03	N/A

Fuente: Elaboración propia.

La Tabla 4 proporciona una comparación de los resultados obtenidos al sintonizar un controlador PID para un convertidor elevador DC-DC. Se evaluaron los resultados utilizando el error cuadrático medio (RMSE) y la respuesta del sistema bajo diferentes condiciones de entrada y carga. Se puede observar que el algoritmo GWO-PID obtuvo el mejor rendimiento, con un RMSE aproximadamente un 50,89% menor que PSO y un 44,70% menor que GA. Además, se puede ver que los algoritmos PSO y GA son más susceptibles de quedar atrapados en soluciones óptimas locales en comparación con el algoritmo GWO. También se debe considerarse que el algoritmo GWO tiene la ventaja de requerir menos parámetros de configuración para el proceso de optimización.

Publicación 2.- Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms.

En la segunda publicación, se presenta un estudio comparativo de desempeño de cuatro algoritmos de optimización bio-inspirados y dos algoritmos tradicionales, en el contexto de la optimización del controlador MPPT de un sistema fotovoltaico de seguimiento del punto de máxima potencia. El estudio se realiza en cuatro escenarios diferentes, que incluyen condiciones constantes y variables de irradiación solar, carga y temperatura. Los resultados obtenidos se presentan en términos de eficiencia, potencia total generada y tiempo de respuesta a cambios de irradiación, así como mediante la evaluación del RMSE entre la potencia de salida obtenida y la potencia de referencia. En la Tabla 5 se muestran los resultados obtenidos para uno de los casos estudiados a profundidad en la segunda publicación del Capítulo 2 de esta tesis por compendio de artículos.

Tabla 5 Comparación de algoritmos de optimización para controlador MPPT de sistemas fotovoltaicos.

Algoritmo	**Eficiencia promedio**	**Potencia neta generada (Wh)**	**RMSE**	**Tiempo de respuesta (s)**
GWO	0.238	8,178.5	25.91	0.0175
PSO	0.219	6,922.3	110.82	0.0270
SA	0.226	7,381.1	77.18	0.0270
WOA	0.233	7,954.1	44.10	0.0280
P&O	0.192	7,954.1	54.98	0.0178
INC	0.231	7,694.7	38.57	0.0420

Fuente: Elaboración propia.

La anterior Tabla 5 resume los resultados de la comparación del desempeño de diferentes algoritmos en la optimización de un controlador de seguimiento del punto de máxima potencia para un sistema fotovoltaico bajo condiciones simuladas de irradiación, temperatura y carga variable. Según los resultados, el algoritmo GWO tuvo el mejor desempeño en términos de eficiencia y potencia generada, siendo en promedio un 3% a 6% mejor que los otros algoritmos evaluados. Además, también demostró tener un tiempo de respuesta más rápido ante cambios en la irradiación solar. Específicamente, el algoritmo GWO generó una potencia neta de 8,178.5 Wh con una eficiencia promedio de 0.238, mientras que el algoritmo PSO generó una potencia neta de 6,922.3 Wh con una eficiencia promedio de 0.219 y el algoritmo SA generó una potencia neta de 7,381.1 Wh con una eficiencia promedio de 0.226.

Es importante mencionar que esta tabla solo resume uno de los casos detallados en la respectiva publicación del Capítulo 2 de la tesis. En el estudio completo, se evaluaron múltiples combinaciones de algoritmos y parámetros para optimizar el controlador de seguimiento del punto de máxima potencia para un sistema fotovoltaico. Los resultados indican que el uso de algoritmos bio-inspirados puede mejorar significativamente el desempeño del sistema de seguimiento del punto de máxima potencia en sistemas fotovoltaicos.

Publicación 3.- Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach.

El tercer artículo presenta un modelo de gestión energética para una microrred híbrida autónomo que utiliza una combinación de optimización por enjambre de partículas y redes neuronales artificiales. La incorporación de una red neuronal en el modelo dinámico permitió obtener estimaciones precisas de los parámetros principales de cada subsistema. Se evaluó el rendimiento del modelo utilizando datos reales y se comparó con las predicciones del modelo antes de utilizar dichos datos. La Tabla 6 muestra los valores obtenidos de RMSE entre datos experimentales y valores predichos por el modelo propuesto basado en redes neuronales optimizadas.

Tabla 6 Resumen de MSE y regresión lineal de la RNA entrenada.

Parámetro	**Modelo basado en RNA optimizada**	
	RMSE	R
Flujo de biomasa (M)	0.0465	0.9944
Flujo de Syngas (Q_{syngas})	0.0393	0.9996
Flujo de aire hacia el motor de combustión interna $(Q_{air_{ICE}})$	0.1194	0.9997
Demanda de energía a la planta de gasificación (P_d)	0.0513	0.9873
Potencia entregada por la planta de gasificación (P_{SGPP})	0.0342	0.9810
Potencia generada por el arreglo FV $(PV_{Generation})$	0.0303	0.9871
Estado de carga del sistema de baterías (SoC)	0.0419	0.9850
Potencia entregada por el Sistema de baterías (BB_{power})	0.0212	0.9960
Predicción de la potencia no servida (P_u)	0.0513	0.9716

Fuente: Elaboración propia.

Los resultados indicaron una buena correlación entre los valores predichos y los valores medidos, con un RMSE promedio del 0,1247 y un MSD del 0,4599. Se identificó que la predicción del SoC del sistema de almacenamiento de energía fue el parámetro más difícil de estimar y se necesitan nuevas variables de entrada para mejorar la precisión de las predicciones de la red neuronal. El modelo propuesto es una alternativa eficaz para la gestión de sistemas eléctricos complejos y dinámicos como las microrredes híbridas basadas en energías renovables, y se propone como trabajo futuro la integración de más subsistemas de generación y almacenamiento de energía y la implementación de un sistema de control automatizado para su gestión y optimización.

Publicación 4.- A multimicrogrid energy management model implementing an evolutionary game-theoretic approach.

El estudio propone un modelo de gestión de energía para un entorno multi-microrred (MMG) utilizando una aproximación evolutiva basada en la teoría de juegos. La investigación presenta un modelo de tres etapas que incluye la selección de modo de operación, gestión de energía en modo aislado y predicción del estado futuro de las microrredes. Los resultados de la investigación muestran que el modelo propuesto es efectivo en la administración de las microrredes y permite la reducción del número de cambios frecuentes de modo de operación. El modelo propuesto en dicha publicación se comparó con otro modelo, donde los autores proponen un sistema gestor de la energía basado prioritariamente en el costo de la energía y del tipo jerarquizado de reglas. La Tabla 7 muestra dicha comparativa.

Tabla 7 Comparativa entre el modelo propuesto gestor multimicrorred y un modelo de la literatura.

Parámetro	**MG EMG basado en prioridades**	**MMG-EMS**
Evaluación de parámetros.	Solo costo.	Carga en MGs, generación de energía y potencia intercambiada.
Modos de operación.	No se mencionan.	Aislado y conectado a la red.
Generación de energía.	Basada en costos.	Energía renovable en ambos modos, mayor en modo conectado a la red.
Carga servida.	Menor número de cargas.	Mayor número de cargas en ambos modos.
Potencia intercambiada.	Intercambio de potencia basado en costos.	Intercambio de potencia óptimo, mayor cantidad de potencia intercambiada.
Algoritmos utilizados.	Optimización no-lineal multiobjetivo.	Redes neuronales, TRFS, QOSOS con teoría de juegos y cadena de Markov.

Fuente: Elaboración propia.

La Tabla 7 resume los principales hallazgos de la comparación entre el sistema anterior de MG EMG basado en prioridades y el sistema de MMG-EMS propuesto. El sistema de MMG-EMS se destaca por su enfoque en la gestión de energía en función de la carga en las microrredes y la consideración de prioridades definidas por los usuarios, en contraste con el sistema anterior, que solo evaluaba los costos para satisfacer la demanda del usuario. Parte central del trabajo de esta cuarta publicación fue el proponer un modelo para la gestión de energía en un entorno de varias microrredes que fueran capaz de actuar en modo coordinado a través de un controlador en miras de mejorar la disponibilidad de energía para los usuarios.

El sistema propuesto MMG-EMS funciona en dos modos, aislado e interconectado a la red, utilizando energía renovable en ambos modos de operación. La generación de energía en el modo conectado a la red es mayor debido a la dependencia de energías renovables con el medio ambiente. Se observó que el sistema de MMG-EMS es capaz de servir una mayor cantidad de cargas en ambos modos y de intercambiar una mayor cantidad de energía de manera óptima.

En términos de algoritmos utilizados, el sistema de MMG-EMS utiliza una variedad de técnicas avanzadas, como redes neuronales, TRFS, QOSOS con teoría de juegos y cadena de Markov, para mejorar la gestión de energía y reducir la cantidad de conmutaciones de modo. En contraste, el sistema anterior solo utiliza un conjunto de reglas de operación previamente definidas, sin capacidad de adaptarse a un entorno cambiante.

A partir de los cuatro estudios revisados en este trabajo de tesis por compendio de artículos, se puede concluir que la aplicación de técnicas de optimización, métodos metaheurísticos y modelos de gestión de energía puede mejorar significativamente la eficiencia, fiabilidad y estabilidad de los sistemas de energía renovable. La integración de algoritmos bioinspirados, como el Grey Wolf Optimizer, y técnicas de inteligencia artificial, como las redes neuronales y la optimización por enjambre de partículas, en los controladores de MPPT en sistemas solares fotovoltaicos ha demostrado una mejora en el rendimiento en comparación con los algoritmos tradicionales, como P&O e INC. Además, la integración de un modelo de gestión de energía de tres etapas en un entorno multi-microrred demostró una mejora en la estabilidad del sistema, a través de la selección óptima de microrredes para el intercambio de energía y la predicción precisa del modo de operación.

En términos de las implicaciones prácticas, estos resultados pueden ser aplicables en la implementación de sistemas de energía renovable en el mundo real, especialmente en la integración de energía renovable en redes inteligentes. La utilización de estos modelos y técnicas puede mejorar la eficiencia y la estabilidad del sistema, así como reducir los costos de energía para los usuarios finales. En términos teóricos, estos estudios demuestran la efectividad de la aplicación de técnicas de inteligencia artificial y optimización en el campo de la gestión de energía en microrredes.

Los cuatro estudios revisados de esta tesis de compendio son originales y rigurosos en su metodología, contribuyendo al desarrollo de un tema relevante en el campo de la gestión de energía renovable. Los resultados obtenidos demuestran la eficacia de las técnicas de optimización y modelos de gestión de energía en la mejora del rendimiento de los sistemas de energía renovable en microrredes, sugiriendo su potencial para aplicaciones prácticas en la industria.

3.2 Trabajos futuros

En los trabajos futuros de investigación de las publicaciones mencionadas, hay varias líneas de investigación que podrían explorarse.

Para la primera publicación, "Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller", una línea de investigación futura podría ser la extensión del análisis de rendimiento a una mayor variedad de sistemas de control y condiciones de funcionamiento. Además, podría explorarse la posibilidad de combinar estos algoritmos de optimización de manera híbrida para mejorar aún más el rendimiento del controlador PID.

Para la segunda publicación, "Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms", una línea de investigación futura podría ser la integración del algoritmo Grey Wolf Optimizer a una plataforma experimental para realización de pruebas y validación de resultados en diferentes condiciones de operación.

Para la tercera publicación, "Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach", una línea de investigación futura podría ser la extensión del modelo de gestión energética a microrredes híbridas más grandes y complejas, y la evaluación de su rendimiento en condiciones de funcionamiento reales. Además, podría explorarse la posibilidad de integrar el modelo con sistemas de control y supervisión avanzados.

Por último, para la cuarta publicación, "A multimicrogrid energy management model implementing an evolutionary game-theoretic approach", una línea de investigación futura podría ser la aplicación y prueba del modelo propuesto en entornos de multi microrredes reales, y la comparación del rendimiento del modelo con otros enfoques de gestión energética. Además, podría explorarse la posibilidad de integrar el modelo con sistemas de comunicación y coordinación avanzados para mejorar la eficiencia.

Además de lo mencionado para cada publicación presentada en esta tesis, es importante considerar como posible trabajo futuro:

- La evaluación de los algoritmos bio-inspirados de optimización en un entorno real, mediante la construcción de una plataforma experimental basada en electrónica de potencia para la validación en físico de los resultados simulados, extender los algoritmos bio-inspirados de optimización a una mayor gama de controladores.

- Añadir una capa extra de filtrado previo a los datos de alimentación de las RNA, explorar el Análisis Topológico de Datos para mejora del desempeño de los datos de alimentación.
- Integrar aspectos de seguridad y protección de datos sensibles para el intercambio de información en el sistema multi microrred que se plantea.

En general, el trabajo futuro de investigación de la presente tesis podría contribuir a mejorar la eficiencia y la resiliencia de los sistemas eléctricos y a impulsar la transición hacia una economía más sostenible y descentralizada.

3.3 Discussió i conclusions

La discussió i les conclusions del present treball d'investigació es divideixen en dues categories, les discussions i les conclusions relacionades amb la millora del control primari de les microxarxes a través de la implementació d'algoritmes d'optimització en la millora dels controladors, i les discussions i conclusions relacionades amb el control secundari i terciari, on es van implementar models per a la gestió òptima de l'energia i l'intercanvi de potència entre les diferents fonts d'una microxarxa, així com en un entorn de dos o més microxarxes. A continuació, es detallen les discussions i conclusions.

Sobre el control primari en aquest projecte d'investigació es va treballar en el model dels convertidors de potència i una estratègia de sintonització dels seus controladors PID mitjançant algoritmes bio-inspirats. Es van emprar els algoritmes de manada de llops (GWO, Grey Wolf Optimizer), enjambre de partícules (PSO, Particle Swarm Optimization) i genètic (GA, Genetic Algorithm) comparant-los amb mètodes clàssics de sintonització com són el mètode de les oscil·lacions sostenides de Ziegler-Nichols per avaluar el rendiment dels controladors PID proposats sota condicions de voltatge d'entrada variable i càrrega canviant. Els convertidors de potència es van modelar matemàticament mitjançant les seues equacions d'espai d'estat i circuit elèctric. La implementació dels models i la seua simulació es va realitzar mitjançant el programa de Matlab/Simulink. Els resultats obtinguts es van avaluar en termes del RMSE entre el valor de sortida de voltatge consigna i el valor de voltatge obtingut per a diferents configuracions i diferents mètodes d'optimització.

D'acord amb els resultats mostrats en les publicacions del Capítol 2 del present treball, en general, els controladors PID sintonitzats mitjançant algoritmes bio-inspirats van mostrar un rendiment millor que aquells sintonitzats per mètodes clàssics, amb l'avantatge extra que l'algoritme bio-inspirat és capaç de buscar solucions més ràpides i fora de l'espai tradicional dels mètodes clàssics. En concret, parlant de controladors de convertidors de potència, l'algoritme GWO va tindre un millor rendiment amb un RMSE un 50,89% menor que el mateix controlador sintonitzat per la PSO i un 44,70% menor que el seu equivalent amb algoritmes GA, i un 63% menor que l'obtingut pel mètode de les oscil·lacions sostenides de Ziegler-Nichols. Es va observar que els algoritmes de PSO i el GA són susceptibles de quedar-se atrapats en òptims locals, mentre que el GWO, en imitar el mecanisme de caça dels llops, és capaç de trobar una solució global més òptima. A més a més, es va observar que el GWO té avantatges computacionals respecte al PSO i GA ja que requereix menys paràmetres de configuració prèvis a l'optimització i menors temps per a la convergència a l'òptim, fins a un 35% més ràpid segons l'algoritme. La Taula 8 resumeix els principals resultats i descobriments d'aquesta investigació sobre algoritmes bio-inspirats aplicats al control primari en una microxarxa elèctrica.

Tabla 8 Resum dels descobriments en l'aplicació d'algoritmes bio-inspirats en el control primari en microxarxes elèctriques.

Control primari	**Algoritmes d'optimització bio-inspirats**
Model dels convertidors de potència	Algoritmes de manada de llops (GWO), enjambres de partícules (PSO) i genètic (GA)
Rendiment dels controladors PID proposats	Millor rendiment que els sintonitzats per mètodes clàssics
Avantatges dels algoritmes bio-inspirats	Capacitat per a buscar solucions més ràpides i fora de l'espai tradicional dels mètodes clàssics, capacitat per a trobar solucions globals i requerir menys paràmetres de configuració prèvis i menors temps per a la convergència a l'òptim
Resultats dels algoritmes d'optimització	GWO va mostrar el millor rendiment amb un RMSE un 50,89% menor que el mateix controlador sintonitzat pel PSO i un 44,70% menor que el seu equivalent amb algoritmes GA, i un 63% menor que el resultat obtingut pel mètode de les oscil·lacions sostenudes de Ziegler-Nichols.

Font: Elaboració pròpia.

En este treball d'investigació sobre el control secundari i terciari de la microxarxa, s'ha dissenyat un nou model en tres etapes d'un sistema de gestió de l'energia per a un entorn de diverses microxarxes. En aquest punt, no només va ser important treballar en la millora de la qualitat de l'energia dins de la microxarxa, cosa que va ser aconseguida mitjançant el control primari, sinó que també es van establir criteris i estratègies per a implementar un Sistema de Gestió de l'Energia (SGE) capaç de (i) seleccionar el mode d'operació de la microxarxa, (ii) gestionar el flux d'energia dins i fora de la microxarxa i (iii) predir estats i requisits futurs de la microxarxa. Per a cadascuna de les tasques anteriors del SGE es van implementar i combinar diverses tècniques metaheurístiques: xarxes neuronals artificials, sistemes de lògica difusa i algoritmes d'optimització bio-inspirats.

El poder determinar adequadament el millor mode d'operació de la microxarxa permet que l'usuari cobrisca la seua demanda d'energia, al mateix temps que s'augmenta la resiliència del sistema habilitant un intercanvi d'energia entre les diferents fonts dins de la microxarxa i fins i tot entre altres microxarxes, segons la metodologia mostrada en els articles científics de la secció prèvia. El model proposat de SGE que implementa tècniques i algoritmes metaheurístics bio-inspirats va demostrar ser eficient i tenir avantatges sobre les tècniques comparades, com ara la possibilitat de trobar solucions fora de l'espai de solucions típics que els algoritmes clàssics abasten, poder ser implementats de manera automàtica sense necessitat d'un exhaustiu anàlisi matemàtic del sistema, entre altres, com es mostra de manera detallada en cadascuna de les publicacions relacionades del Capítol 2.

En el cas que les microxarxes de l'entorn multi-microxarxa no puguen proveir energia a causa de pobres condicions ambientals, llavors les microxarxes entraran mitjançant una ordre d'un controlador central que alberga el SEG a un mode operació en interconnexió amb la xarxa elèctrica per a proveir d'energia als seus usuaris i així cobrir la demanda d'energia. En la Taula 9 es detallen algunes de les principals característiques del SGE desenvolupat per al control secundari i terciari en una microxarxa.

Tabla 9 Principals característiques del SGE desenvolupat.

Control secundari y terciario	**Tècniques metaheurístiques**
Model en tres etapes d'un sistema de gestió de l'energia	Xarxes neuronals artificials, sistemes de lògica difusa i algoritmes d'optimització bio-inspirats
Funcions del Sistema de Gestió de l'Energia	Seleccionar el mode d'operació de la microxarxa, gestionar el flux d'energia dins i fora de la microxarxa, predir estats i requisits futurs de la microxarxa
Avantatges del model proposat de SGE	Eficiència i capacitat per a trobar solucions fora de l'espai de solucions típics que els algoritmes clàssics abasten, possibilitat de ser implementat de manera automàtica sense necessitat d'un exhaustiu anàlisi matemàtic del sistema
Mode d'interconnexió amb la xarxa elèctrica	Si les microxarxes no poden proveir energia a causa de pobres condicions ambientals

Font: Elaboració pròpia.

La Taula 9 anterior mostra un resum de les característiques del SGE presentat en aquesta investigació per a una microxarxa, el qual és capaç de seleccionar el mode d'operació, gestionar el flux d'energia i predir estats i requeriments futurs. Les tècniques implementades es detallen en les respectives publicacions del Capítol 2 d'aquesta investigació. Els resultats indiquen que la combinació d'aquestes tècniques metaheurístiques en el model proposat de SGE va permetre trobar solucions més eficients i fora de l'espai de solucions típics que els algoritmes clàssics abasten, el que resulta en una major resiliència del sistema i una millor gestió de l'energia dins de la microxarxa.

Sobre les troballes particulars en cadascuna de les publicacions, a continuació es presenta un breu resum i discussió.

Publicaciò 1.- Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller.

En aquesta publicació es va presentar un estudi comparatiu del rendiment de tres algoritmes metaheurístics per a l'optimització d'un controlador PID per a un convertidor boost de CC-CC. El treball mostra com la implementació dels algoritmes PSO, GA i GWO va permetre trobar valors òptims per al controlador a través de la simulació del sistema en MATLAB/Simulink. Els resultats obtinguts van permetre determinar quin dels tres algoritmes va proporcionar el millor rendiment per a l'aplicació específica del convertidor boost i com cada un d'ells pot ser més o menys susceptible a caure en solucions òptimes locals o globals. Aquest treball pot resultar de gran interès per al disseny i optimització de controladors per a convertidors de potència.

Tabla 10 Comparació del rendiment dels algoritmes PSO, GA i GWO en la sintonització d'un controlador PID per a un convertidor Boost DC-DC.

Algoritme	**RMSE (%)**	**Diferència amb GWO (%)**
PSO	20.43	50.89%
GA	18.29	44.70%
GWO	10.03	N/A

Fuente: Elaboración propia.

La Taula 10 proporciona una comparació dels resultats obtinguts en la sintonització d'un controlador PID per a un convertidor elevador DC-DC. Es van avaluar els resultats utilitzant l'error quadràtic mitjà (RMSE) i la resposta del sistema sota diferents condicions d'entrada i càrrega. Es pot observar que l'algoritme GWO-PID va obtenir el millor rendiment, amb un RMSE aproximadament un 50,89% menor que PSO i un 44,70% menor que GA. A més, es pot veure que els algoritmes PSO i GA són més susceptibles de quedar atrapats en solucions òptimes locals en comparació amb l'algoritme GWO. També s'ha de considerar que l'algoritme GWO té l'avantatge de requerir menys paràmetres de configuració per al procés d'optimització.

Publicaciò 2.- Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms.

En la segona publicació, es presenta un estudi comparatiu de rendiment de quatre algoritmes d'optimització bio-inspirats i dos algoritmes tradicionals, en el context de l'optimització del controlador MPPT d'un sistema fotovoltaic de seguiment del punt de màxima potència. L'estudi es realitza en quatre escenaris diferents, que inclouen condicions constants i variables d'irradiació solar, càrrega i temperatura. Els resultats obtinguts es presenten en termes d'eficiència, potència total generada i temps de resposta a canvis d'irradiació, així com mitjançant l'avaluació del RMSE entre la potència de sortida obtinguda i la potència de referència. En la Taula 11 es mostren els resultats obtinguts per a un dels casos estudiats en profunditat en la segona publicació del Capítol 2 d'aquesta tesi per compendi d'articles.

Tabla 11 Comparació d'algoritmes d'optimització per a controlador MPPT de sistemes fotovoltaics.

Algoritme	Eficiència promig	Potència neta generada (Wh)	RMSE	Temps de resposta (s)
GWO	0.238	8,178.5	25.91	0.0175
PSO	0.219	6,922.3	110.82	0.0270
SA	0.226	7,381.1	77.18	0.0270
WOA	0.233	7,954.1	44.10	0.0280
P&O	0.192	7,954.1	54.98	0.0178
INC	0.231	7,694.7	38.57	0.0420

Font: Elaboració pròpia.

La anterior Taula 11 resume els resultats de la comparació del rendiment de diferents algoritmes en l'optimització d'un controlador de seguiment del punt de màxima potència per a un sistema fotovoltaic sota condicions simulades d'irradiació, temperatura i càrrega variable. Segons els resultats, l'algoritme GWO va tindre el millor rendiment en termes d'eficiència i potència generada, sent en promig un 3% a 6% millor que els altres algoritmes avaluats. A més, també va demostrar tindre un temps de resposta més ràpid davant canvis en la irradiació solar. Específicament, l'algoritme GWO va generar una potència neta de 8,178.5 Wh amb una eficiència promig de 0.238, mentre que l'algoritme PSO va generar una potència neta de 6,922.3 Wh amb una eficiència promig de 0.219 i l'algoritme SA va generar una potència neta de 7,381.1 Wh amb una eficiència promig de 0.226. És important mencionar que aquesta taula només resumeix un dels casos detallats en la respectiva publicació del Capítol 2 de la tesi. En l'estudi complet, es van avaluar múltiples combinacions d'algoritmes i paràmetres per a optimitzar el controlador de seguiment del punt de màxima potència per a un sistema fotovoltaic. Els resultats indiquen que l'ús d'algoritmes bio-inspirats pot millorar significativament el rendiment del sistema de seguiment del punt de màxima potència en sistemes fotovoltaics.

Publicaciò 3.- Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach.

El tercer article presenta un model de gestió energètica per a una microrred híbrida autònoma que utilitza una combinació d'optimització per enjambres de partícules i xarxes neuronals artificials. La incorporació d'una xarxa neuronal en el model dinàmic va permetre obtenir estimacions precisos dels paràmetres principals de cada subsistema. Es va avaluar el rendiment del model utilitzant dades reals i es va comparar amb les prediccions del model abans d'utilitzar aquestes dades. La Taula 12 mostra els valors obtinguts de RMSE entre dades experimentals i valors predits pel model proposat basat en xarxes neuronals optimitzades.

Tabla 12 Resum de MSE i regressió lineal de la RNA entrenada.

Paràmetre	**Model basat en RNA optimitzada**	
	RMSE	R
Flux de biomassa(M)	0.0465	0.9944
Flux de Syngas (Q_{syngas})	0.0393	0.9996
Flux d' aire cap al motor de combustió interna $(Q_{air_{ICE}})$	0.1194	0.9997
Demanda d' energia a la planta de gasificació (P_d)	0.0513	0.9873
Potència lliurada per la planta de gasificació(P_{SGPP})	0.0342	0.9810
Potència generada per l' arranjament FV ($PV_{Generation}$)	0.0303	0.9871
Estat de càrrega del sistema de bateries (SoC)	0.0419	0.9850
Potència lliurada pel Sistema de bateries(BB_{power})	0.0212	0.9960
Predicció de la potència no servida (P_u)	0.0513	0.9716

Font: Elaboració pròpia.

Els resultats van indicar una bona correlació entre els valors predits i els valors mesurats, amb un RMSE promig de 0,1247 i un MSD de 0,4599. Es va identificar que la predicció del SoC del sistema d'emmagatzematge d'energia va ser el paràmetre més difícil d'estimar i es necessiten noves variables d'entrada per millorar la precisió de les prediccions de la xarxa neuronal. El model proposat és una alternativa eficaç per a la gestió de sistemes elèctrics complexos i dinàmics com les microrredes híbrides basades en energies renovables, i es proposa com a treball futur la integració de més subsistemes de generació i emmagatzematge d'energia i la implementació d'un sistema de control automatitzat per a la seva gestió i optimització.

Publicació 4.- A multimicrogrid energy management model implementing an evolutionary game-theoretic approach.

La investigació proposa un model de gestió d'energia per a un entorn multimicroxarxa (MMG) utilitzant una aproximació evolutiva basada en la teoria de jocs. La investigació presenta un model de tres etapes que inclou la selecció del mode d'operació, gestió d'energia en mode aïllat i predicció de l'estat futur de les microxarxes. Els resultats de la investigació mostren que el model proposat és efectiu en l'administració de les microxarxes i permet la reducció del nombre de canvis freqüents de mode d'operació. El model proposat en aquesta publicació es va comparar amb un altre model, on els autors proposen un sistema gestor d'energia basat prioritariament en el cost de l'energia i del tipus jerarquitzat de regles. La Taula 13 mostra aquesta comparativa.

Tabla 13 Comparativa entre el model propost gestor multimicroxarxa i un model de la literatura.

Paràmetre	**MG EMG basat en prioritats**	**MMG-EMS**
Avaluació de paràmetres.	Només cost.	Càrrega en MGs, generació d'energia i potència intercanviada.
Modes d'operació.	No es mencionen.	Aïllat i connectat a la xarxa.
Generació d'energia.	Basat en costes.	Energia renovable en ambdós modes, major en mode connectat a la xarxa.
Càrrega servida.	Menor nombre de càrregues.	Major nombre de càrregues en ambdós modes.
Potència intercanviada.	Intercanvi de potència basat en costos.	Intercanvi de potència òptim, major quantitat de potència intercanviada.
Algorismes utilitzats.	Optimització no-lineal multiobjectiu.	Xarxes neuronals, TRFS, QOSOS amb teoria de jocs i cadena de Markov.

Font: Elaboració pròpia.

La Taula 13 resumeix els principals resultats de la comparació entre el sistema anterior de MG EMG basat en prioritats i el sistema de MMG-EMS proposat. El sistema de MMG-EMS es destaca pel seu enfocament en la gestió d'energia en funció de la càrrega en les microrredes i la consideració de prioritats definides pels usuaris, en contrast amb el sistema anterior, que només avaluava els costos per satisfer la demanda de l'usuari. La part central del treball d'aquesta quarta publicació va ser proposar un model per a la gestió d'energia en un entorn de diverses microrredes que fos capaç d'actuar de manera coordinada a través d'un controlador per millorar la disponibilitat d'energia per als usuaris. El sistema proposat MMG-EMS funciona en dos modes, aïllat i interconnectat a la xarxa, utilitzant energia renovable en ambdós modes d'operació. La generació d'energia en el mode interconnectat a la xarxa és major degut a la dependència d'energies renovables amb el medi ambient. Es va observar que el sistema de MMG-EMS és capaç de servir una major quantitat de càrregues en ambdós modes i d'intercanviar una major quantitat d'energia de manera òptima. En termes d'algoritmes utilitzats, el sistema de MMG-EMS utilitza una varietat de tècniques avançades, com ara xarxes neuronals, TRFS, QOSOS amb teoria de jocs i cadena de Markov, per millorar la gestió d'energia i reduir la quantitat de commutacions de mode. En contrast, el sistema anterior només utilitza un conjunt de regles d'operació prèviament definides, sense capacitat d'adaptar-se a un entorn canviant.

A partir dels quatre estudis revisats en aquest treball de tesi per compendi d'articles, es pot concloure que l'aplicació de tècniques d'optimització, mètodes metaheurístics i models de gestió d'energia pot millorar significativament l'eficiència, fiabilitat i estabilitat dels sistemes d'energia renovable. La integració d'algoritmes bioinspirats, com el Grey Wolf Optimizer, i tècniques d'intel·ligència artificial, com les xarxes neuronals i l'optimització per enjambres de partícules, en els controladors de MPPT en sistemes solars fotovoltaics ha demostrat una millora en el rendiment en comparació amb els algoritmes tradicionals, com P&O i INC. A més, la integració d'un model de gestió d'energia de tres etapes en un entorn multimicrorred demostra una millora en l'estabilitat del sistema, a través de la selecció òptima de microrredes per a l'intercanvi d'energia i la predicció precisa del mode d'operació.

En termes d'implicacions pràctiques, aquests resultats poden ser aplicables en la implementació de sistemes d'energia renovable en el món real, especialment en la integració d'energia renovable en xarxes intel·ligents. L'utilització d'aquests models i tècniques pot millorar l'eficiència i l'estabilitat del sistema, així com reduir els costos d'energia per als usuaris finals. En termes teòrics, aquests estudis demostren l'efectivitat de l'aplicació de tècniques d'intel·ligència artificial i optimització en el camp de la gestió d'energia en microrredes.

Els quatre estudis revisats d'aquesta tesi de compendi són originals i rigurosos en la seva metodologia, contribuint al desenvolupament d'un tema rellevant en el camp de la gestió d'energia renovable. Els resultats obtinguts demostren l'eficàcia de les tècniques d'optimització i models de gestió d'energia en la millora del rendiment dels sistemes d'energia renovable en microrredes, suggerint el seu potencial per a aplicacions pràctiques en la indústria.

3.4 Treballs futurs

En els treballs futurs d'investigació de les publicacions mencionades, hi ha diverses línies d'investigació que podrien ser explorades.

Per a la primera publicació, "Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller", una línia d'investigació futura podria ser l'extensió de l'anàlisi de rendiment a una major varietat de sistemes de control i condicions de funcionament. A més, es podria explorar la possibilitat de combinar aquests algoritmes d'optimització de manera híbrida per millorar encara més el rendiment del controlador PID.

Per a la segona publicació, "Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms", una línia d'investigació futura podria ser la integració de l'algoritme Grey Wolf Optimizer a una plataforma experimental per a la realització de proves i validació de resultats en diferents condicions d'operació.

Per a la tercera publicació, "Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach", una línia d'investigació futura podria ser l'extensió del model de gestió energètica a microrreds híbrides més grans i complexes, i l'avaluació del seu rendiment en condicions de funcionament reals. A més, es podria explorar la possibilitat d'integrar el model amb sistemes de control i supervisió avançats.

Finalment, per a la quarta publicació, "Un model de gestió energètica de multimicroxarxa implementant un enfocament de teoria del joc evolutiu", una línia de recerca futura podria ser l'aplicació i prova del model proposat en entorns de multimicroxarxes reals, i la comparació del rendiment del model amb altres enfocaments de gestió energètica. A més, es podria explorar la possibilitat d'integrar el model amb sistemes de comunicació i coordinació avançats per a millorar l'eficiència.

A més de les coses mencionades per a cada publicació presentada en aquesta tesi, és important considerar com a possible treball futur:

- Avaluació dels algorismes bioinspirats d'optimització en un entorn real, construint una plataforma experimental basada en electrònica de potència per a la validació física dels resultats simulats, i ampliant els algorismes bioinspirats d'optimització a una major gamma de controladors.

- Afegir una capa extra de filtratge previ a les dades d'alimentació de les RNA, explorant l'Anàlisi Topològica de Dades per a la millora del rendiment de les dades d'alimentació.
- Integrar aspectes de seguretat i protecció de dades sensibles per a l'intercanvi d'informació en el sistema multimicroxarxa que es planteja.

En general, el treball futur de recerca d'aquesta tesi podria contribuir a millorar l'eficiència i la resiliència dels sistemes elèctrics i impulsar la transició cap a una economia més sostenible i descentralitzada.

3.5 Discussion and Conclusions

The discussion and conclusions of this research work are divided into two categories: discussions and conclusions related to the improvement of primary control in microgrids through the implementation of optimization algorithms in controller tuning, and discussions and conclusions related to secondary and tertiary control, where models were implemented for optimal energy management and power exchange among different sources in a microgrid, as well as in an environment of two or more microgrids. The discussions and conclusions are detailed below.

In this research project, the primary control was focused on the power converter model and a tuning strategy for its PID controllers using bio-inspired algorithms. Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) were employed and compared to classical tuning methods such as Ziegler-Nichols sustained oscillations method to evaluate the performance of the proposed PID controllers under variable input voltage and changing load conditions. The power converters were mathematically modeled using state-space equations and electrical circuit equations. The models were implemented and simulated using Matlab/Simulink. The results were evaluated in terms of the Root Mean Square Error (RMSE) between the reference voltage output and the obtained voltage value for different configurations and optimization methods.

According to the results presented in Chapter 2, the PID controllers tuned using bio-inspired algorithms showed better performance than those tuned using classical methods, with the added advantage that the bio-inspired algorithm is capable of searching for solutions more quickly and outside the traditional space of classical methods. Specifically, in the case of power converter controllers, the GWO algorithm performed better with an RMSE that was 50.89% lower than the same controller tuned by PSO and 44.70% lower than its equivalent with GA algorithms, and 63% lower than that obtained by the Ziegler-Nichols sustained oscillations method. It was observed that the PSO and GA algorithms are susceptible to getting trapped in local optima, while the GWO, by imitating the hunting mechanism of wolves, is capable of finding a better global solution. Additionally, it was observed that the GWO has computational advantages over PSO and GA, as it requires fewer prior configuration parameters for optimization and takes less time to converge to the optimum, up to 35% faster, depending on the algorithm. Table 14 summarizes the main results and findings of this research on bio-inspired algorithms applied to primary control in an electric microgrid.

Tabla 14 Summary of findings in the application of bio-inspired algorithms in primary control in electrical microgrids.

Primary control	Bio-inspired optimization algorithms
Model of power converters	Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO) and Genetic (GA) algorithms.
Performance of proposed PID controllers	Better performance than those tuned by classical methods.
Advantages of bio-inspired algorithms	Ability to search for faster solutions and outside the traditional space of classical methods, ability to find global solutions and require fewer previous configuration parameters and shorter times for convergence to the optimal.
Results of optimization algorithms	GWO showed the best performance with an RMSE 50.89% lower than the same controller tuned by the PSO and 44.70% lower than its equivalent with GA algorithms, and 63% lower than that obtained by the Ziegler-Nichols sustained oscillations method

Source: Authors.

Regarding the work on secondary and tertiary control of the microgrid in this research, a new three-stage model of an energy management system was designed for a multi-microgrid environment. At this point, it was not only important to work on improving the quality of energy within the microgrid, which was achieved through primary control, but also to establish criteria and strategies for implementing an Energy Management System (EMS) capable of (i) selecting the microgrid's operating mode, (ii) managing the flow of energy within and outside the microgrid, and (iii) predicting future states and requirements of the microgrid. For each of the above EMS tasks, various metaheuristic techniques were implemented and combined: artificial neural networks, fuzzy logic systems, and bio-inspired optimization algorithms. Properly determining the best mode of operation of the microgrid allows the user to meet their energy demand while increasing the system's resilience by enabling energy exchange between different sources within the microgrid and even between other microgrids, as shown in the scientific articles in the previous section. The proposed EMS model implementing bio-inspired metaheuristic techniques and algorithms proved to be efficient and have advantages over compared techniques, such as the possibility of finding solutions outside the typical solution space covered by classical algorithms and being implementable automatically without requiring an exhaustive mathematical analysis of the system, among others, as detailed in each of the related publications in Chapter 2. In the event that the microgrids in the multi-microgrid environment cannot provide energy due to poor environmental conditions, the microgrids will enter into interconnection mode with the power grid through a central controller housing the EMS to provide energy to their users and meet the energy demand. Table 15 details some of the main characteristics of the EMS developed for secondary and tertiary control in a microgrid.

Tabla 15 Main characteristics of the developed EMS.

Secondary and tertiary control	**Metaheuristic techniques**
Three-stage model of an energy management system.	Artificial neural networks, fuzzy logic systems, and bio-inspired optimization algorithms.
Functions of the Energy Management System.	Select the microgrid's operating mode, manage the flow of energy within and outside the microgrid, predict future states and requirements of the microgrid.
Advantages of the proposed EMS model.	Efficiency and ability to find solutions outside the typical solution space covered by classical algorithms, possibility of being implemented automatically without requiring an exhaustive mathematical analysis of the system.
Interconnection mode with the power grid.	If the microgrids cannot provide energy due to poor environmental conditions.

Source: Authors.

The previous Table 15 shows a summary of the characteristics of the EMS presented in this research for a microgrid, which is capable of selecting the operating mode, managing the flow of energy, and predicting future states and requirements. The implemented techniques are detailed in the respective publications of Chapter 2 of this research. The results indicate that the combination of these metaheuristic techniques in the proposed EMS model allowed for finding more efficient solutions outside the typical solution space covered by classical algorithms, resulting in greater system resilience and better energy management within the microgrid. Regarding the particular findings in each of the publications, a brief summary and discussion are presented below.

Publication 1.- Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller.

This publication presents a comparative study of the performance of three metaheuristic algorithms for optimizing a PID controller for a DC-DC boost converter. The study shows how the implementation of PSO, GA, and GWO algorithms allowed for finding optimal values for the controller through system simulation in MATLAB/Simulink. The results obtained allowed determining which of the three algorithms provided the best performance for the specific application of the boost converter and how each of them can be more or less susceptible to falling into local or global optimal solutions. This work may be of great interest for the design and optimization of controllers for power converters.

Tabla 16 Comparison of the performance of PSO, GA and GWO algorithms in tuning a PID controller for a Boost DC-DC converter.

Algorithm	RMSE (%)	Difference with GWO (%)
PSO	20.43	50.89%
GA	18.29	44.70%
GWO	10.03	N/A

Source: Authors.

Table 16 provides a comparison of the results obtained when tuning a PID controller for a DC-DC boost converter. The results were evaluated using the root mean square error (RMSE) and system response under different input and load conditions. It can be observed that the GWO-PID algorithm achieved the best performance, with an RMSE approximately 50.89% lower than PSO and 44.70% lower than GA. Additionally, it can be seen that the PSO and GA algorithms are more susceptible to getting trapped in local optimal solutions compared to the GWO algorithm. It should also be considered that the GWO algorithm has the advantage of requiring fewer configuration parameters for the optimization process.

Publication 2.- Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms.

The second publication presents a comparative study of the performance of four bio-inspired optimization algorithms and two traditional algorithms, in the context of optimizing the MPPT controller of a maximum power point tracking photovoltaic system. The study is carried out in four different scenarios, including constant and variable conditions of solar irradiation, load, and temperature. The results obtained are presented in terms of efficiency, total generated power, and response time to changes in irradiation, as well as through the evaluation of the RMSE between the obtained output power and the reference power. Table 17 shows the results obtained for one of the cases studied in-depth in the second publication of Chapter 2 of this thesis by compilation of articles.

Tabla 17 Comparison of optimization algorithms of MPPT controller for photovoltaic systems.

Algorithm	Average efficiency	Power generated (Wh)	RMSE	Response time (s)
GWO	0.238	8,178.5	25.91	0.0175
PSO	0.219	6,922.3	110.82	0.0270
SA	0.226	7,381.1	77.18	0.0270
WOA	0.233	7,954.1	44.10	0.0280
P&O	0.192	7,954.1	54.98	0.0178
INC	0.231	7,694.7	38.57	0.0420

Source: Authors.

The previous Table 17 summarizes the results of the comparison of the performance of different algorithms in optimizing a maximum power point tracking controller for a photovoltaic system under simulated conditions of irradiation, temperature, and variable load. According to the results, the GWO algorithm had the best performance in terms of efficiency and generated power, being on average 3% to 6% better than the other evaluated algorithms. Additionally, it also demonstrated a faster response time to changes in solar irradiation. Specifically, the GWO algorithm generated a net power of 8,178.5 Wh with an average efficiency of 0.238, while the PSO algorithm generated a net power of 6,922.3 Wh with an average efficiency of 0.219 and the SA algorithm generated a net power of 7,381.1 Wh with an average efficiency of 0.226.

It is important to mention that this table only summarizes one of the cases detailed in the respective publication of Chapter 2 of the thesis. In the complete study, multiple combinations of algorithms and parameters were evaluated to optimize the maximum power point tracking controller for a photovoltaic system. The results indicate that the use of bio-inspired algorithms can significantly improve the performance of the maximum power point tracking system in photovoltaic systems.

Publication 3.- Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach.

The third article presents an energy management model for an autonomous hybrid microgrid that uses a combination of particle swarm optimization and artificial neural networks. The incorporation of a neural network in the dynamic model allowed for obtaining accurate estimates of the main parameters of each subsystem. The performance of the model was evaluated using real data and compared with the predictions of the model before using such data. Table 18 shows the obtained values of RMSE between experimental data and predicted values by the proposed model based on optimized neural networks.

Tabla 18 Summary of MSE and linear regression of trained ANN.

Parameter	**Optimized RNA-based model**	
	RMSE	R
Biomass flow(M)	0.0465	0.9944
Syngas flow (Q_{syngas})	0.0393	0.9996
Airflow to the internal combustion engine $(Q_{air_{ICE}})$	0.1194	0.9997
Power demand to the gasification plant (P_d)	0.0513	0.9873
Power delivered by the gasification plant(P_{SGPP})	0.0342	0.9810
Power generated by the PV array $(PV_{Generation})$	0.0303	0.9871
Battery system state of charge (SoC)	0.0419	0.9850
Power delivered by the Battery System(BB_{power})	0.0212	0.9960
Prediction of power not served (P_u)	0.0513	0.9716

Source: Authors.

The results indicated a good correlation between the predicted and measured values, with an average RMSE of 0.1247 and an MSD of 0.4599. It was identified that the prediction of the SoC of the energy storage system was the most difficult parameter to estimate and new input variables are needed to improve the accuracy of neural network predictions. The proposed model is an effective alternative for the management of complex and dynamic electrical systems such as hybrid microgrids based on renewable energies, and it is proposed as future work the integration of more generation and energy storage subsystems and the implementation of an automated control system for its management and optimization.

Publication 4.- A multimicrogrid energy management model implementing an evolutionary game-theoretic approach.

The study proposes an energy management model for a multi-microgrid (MMG) environment using an evolutionary approach based on game theory. The research presents a three-stage model that includes mode selection, energy management in isolated mode, and prediction of the future state of the microgrids. The results of the research show that the proposed model is effective in the management of microgrids and allows for the reduction of frequent mode changes. The model proposed in this publication was compared with another model, where the authors propose an energy management system based primarily on energy cost and a hierarchical rule-based system. Table 19 shows this comparison.

Tabla 19 Comparison between the proposed multimicrogrid manager model and a model from the literature.

Parameter	**MG EMG based on priorities**	**MMG-EMS**
Parameter evaluation.	Only cost.	Load in MGs, energy generation and exchanged power.
Operating modes.	Not mentioned.	Isolated and grid-connected.
Energy generation	Based on cost.	Renewable energy in both modes, higher in grid-connected mode.
Served load.	Lower number of loads.	Higher number of loads in both modes.
Exchanged power.	Power exchange based on cost.	Optimal power exchange, higher amount of exchanged power.
Algorithms used	Non-linear multi-objective optimization.	Neural networks, TRFS, QOSOS with game theory and Markov chain.

Source: Authors.

The Table 19 summarizes the main findings of the comparison between the previous MG EMG-based priority system and the proposed MMG-EMS system. The MMG-EMS system stands out for its approach to energy management based on load in the microgrids and consideration of user-defined priorities, in contrast to the previous system, which only evaluated costs to meet user demand. The central part of the work of this fourth publication was to propose a model for energy management in a multi-microgrid environment that could act in a coordinated mode through a controller to improve the availability of energy for users.

The proposed MMG-EMS system operates in two modes, isolated and interconnected to the grid, using renewable energy in both operating modes. The energy generation in the grid-connected mode is higher due to the dependence of renewable energies on the environment. It was observed that the MMG-EMS system is capable of serving a greater number of loads in both modes and exchanging a greater amount of energy optimally.

In terms of algorithms used, the MMG-EMS system uses a variety of advanced techniques, such as neural networks, TRFS, QOSOS with game theory, and Markov chain, to improve energy management and reduce the number of mode switches. In contrast, the previous system only uses a set of pre-defined operating rules, without the ability to adapt to a changing environment.

Based on the four reviewed studies in this thesis by article compilation, it can be concluded that the application of optimization techniques, metaheuristic methods, and energy management models can significantly improve the efficiency, reliability, and stability of renewable energy systems. The integration of bio-inspired algorithms, such as the Grey Wolf Optimizer, and artificial intelligence techniques, such as neural networks and particle swarm optimization, in MPPT controllers in photovoltaic solar systems has demonstrated performance improvement compared to traditional algorithms such as P&O and INC. Additionally, the integration of a three-stage energy management model in a multimicrogrid environment demonstrated improved system stability through the optimal selection of microgrids for energy exchange and accurate prediction of the operating mode.

In terms of practical implications, these results may be applicable in the implementation of renewable energy systems in the real world, particularly in the integration of renewable energy in smart grids. The utilization of these models and techniques can improve system efficiency and stability, as well as reduce energy costs for end-users. In theoretical terms, these studies demonstrate the effectiveness of the application of artificial intelligence and optimization techniques in the field of energy management in microgrids.

The four reviewed studies in this article compilation thesis are original and rigorous in their methodology, contributing to the development of a relevant topic in the field of renewable energy management. The results obtained demonstrate the efficacy of optimization techniques and energy management models in improving the performance of renewable energy systems in microgrids, suggesting their potential for practical applications in the industry.

3.6 Future work

In the future research work of the aforementioned publications, there are several lines of research that could be explored.

For the first publication, "Particle Swarm Optimization, Genetic Algorithm, and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller," a future line of research could be the extension of performance analysis to a wider range of control systems and operating conditions. Additionally, the possibility of combining these optimization algorithms in a hybrid manner could be explored to further improve the performance of the PID controller.

For the second publication, "Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms," a future line of research could be the integration of the Grey Wolf Optimizer algorithm into an experimental platform for testing and validation of results under different operating conditions.

For the third publication, "Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach," a future line of research could be the extension of the energy management model to larger and more complex hybrid microgrids and the evaluation of its performance under real operating conditions. Additionally, the possibility of integrating the model with advanced control and supervision systems could be explored.

Finally, for the fourth publication, "A multimicrogrid energy management model implementing an evolutionary game-theoretic approach," a future line of research could be the application and testing of the proposed model in real multimicrogrid environments and the comparison of the performance of the model with other energy management approaches. Additionally, the possibility of integrating the model with advanced communication and coordination systems to improve efficiency could be explored.

In addition to what has been mentioned for each publication presented in this thesis, it is important to consider as a possible future work:

- Evaluating the bio-inspired optimization algorithms in a real environment by setting up a power electronics-based experimental testbed for physical validation of simulated results and extending the bio-inspired optimization algorithms to a wider range of controllers.
- Adding an extra layer of pre-filtering to the feed data of the ANNs, exploring Topological Data Analysis to improve the performance of the feed data.

- Integrating aspects of security and protection of sensitive data for information exchange in the proposed multimicrogrid system.

In general, the future research work of this thesis could contribute to improving the efficiency and resilience of electrical systems and driving the transition to a more sustainable and decentralized economy.

Capítulo 4. Otras publicaciones y actividades

A continuación, se muestra el total de actividades científicas y académicas realizadas a lo largo del periodo en que se llevó a cabo el presente trabajo de investigación, algunas de ellas en revistas indexadas en el JCR, pero no incluidas en el compendio de esta tesis.

Estancias de investigación

Universidad de Guadalajara, Jalisco, México. Estancia realizada del día 16 de enero al 15 de julio del año 2022. Durante esta estancia se realizaron las siguientes actividades:

- Impartición de la materia Teoría de Control.
- Impartición de la materia de Sistemas Eléctricos.
- Organización de eventos de divulgación: Administración de tiempo de vida remanente de convertidores de potencia modulares ventajas y efectos colaterales adversos.
- Análisis de resultados y redacción de artículo científico "Energy Management Model for a Standalone Hybrid Microgrid through a Particle Swarm Optimization and Artificial Neural Networks Approach" recientemente publicado (septiembre 2022) en la revista Energy Conversion and Management (JCR, Q1) con el DOI https://doi.org/10.1016/j.enconman.2022.115920
- Obtención y análisis de resultados, y redacción de artículo científico "Solar photovoltaic Maximum Power Point Tracking controller optimization using Grey Wolf Optimizer: A performance comparison between bio-inspired and traditional algorithms" aceptado para su publicación (enero 2023) en la revista Expert Systems with Applications (JCR, Q1) accesible online con el DOI https://doi.org/10.1016/j.eswa.2022.118700

Proyectos

- **Prosume – Modelado, experimentación y desarrollo de sistemas de gestión óptima de microrredes híbridas renovables (CIGE/2021/172)**

  (2022 – actualidad, Valencia, España)

  Este proyecto está financiado por la Generalitat Valenciana, la entidad participante es la Universitat Politècnica de Valencia. Mi aporte en este proyecto se centra en mi experiencia en modelado y optimización de sistemas energéticos mediante algoritmos bio-inspirados de optimización, lo que me permite contribuir en el diseño y desarrollo de un sistema de gestión óptima para microrredes híbridas renovables. Este proyecto tiene como objetivo desarrollar soluciones innovadoras y eficientes para la gestión de energía renovable, lo que contribuirá a la implementación de soluciones más sostenibles en el ámbito energético

- **Diseño, implementación y fortalecimiento de sistemas de energía solar para mitigar la pérdida de productos agrícolas y revalorizar cadenas hortícolas en Zacatecas.**

  (2022 – actualidad, Zacatecas, México)

  Este proyecto se desarrolla en el marco de los Proyectos Estratégicos (PRONACES) del Consejo Nacional de Ciencia y Tecnología (CONACYT) de México, proyecto social 319195.

El objetivo general de incidencia de este proyecto es contribuir a transitar hacia una matriz energética sostenible mediante el diseño, implementación y fortalecimiento de sistemas de secado solar, con el propósito de minimizar la pérdida de productos hortícolas y agregar valor en las cadenas agroalimentarias del estado de Zacatecas, con la finalidad de coadyuvar a garantizar la soberanía alimentaria y el desarrollo territorial con menor impacto ambiental. Así mismo, se busca investigar estrategias tecnológicas de energía solar, dinámica de cadenas agroalimentarias, situación social de los actores y funcionamiento institucional, mediante la implementación de soluciones integrales para la apropiación de sistemas energéticos resilientes y diversificados distintos a los combustibles fósiles, para lograr beneficios sociales, ambientales y económicos tangibles en los actores de incidencia del proyecto. Colaboro como parte del colectivo de investigación para el diseño y validación de plantas piloto termosolares y prototipos de colectores solares.

- **Rehabilitación de la Red Sismológica y Acelerométrica de Jalisco (RESAJ) de la Universidad de Guadalajara.**
  (2021 – actualidad, Guadalajara, México)
  Este proyecto tiene por objetivo principal la rehabilitación de las estaciones de monitoreo sísmico de la Universidad de Guadalajara a lo largo del territorio de Jalisco con la finalidad de contar con información en tiempo real de movimientos telúricos en nuestra entidad. Parte de las actividades de rehabilitación de la RESAJ es la configuración y programación de equipos adquisidores de datos y la gestión de la base de datos mediante el software especializado Antelope, actividades en las que actualmente colaboro. La información que se obtendrá de esta red será de vital importancia no solo para cuestiones de monitoreo, alarma y caracterización de los eventos sísmicos, sino que será posible realizar labores de investigación en modelación y predicción de eventos.
- **Caracterización de los Acuíferos del Área Metropolitana de Guadalajara.**
  (2019 – 2021, Guadalajara, México)
  Este proyecto se desarrolló en conjunto con el Instituto de Planeación y Gestión del Desarrollo del Área Metropolitana de Guadalajara (IMEPLAN) y la Universidad de Guadalajara. Su objetivo principal fue el análisis diagnóstico sobre el panorama del conocimiento hidrológico actual del Área Metropolitana de Guadalajara. Tuve participación dentro del equipo de trabajo para la revisión y edición del documento, coordinado por la Dra. Edith Xio Mara García, responsable del proyecto, y la Dra. Ana Luz Quintanilla Montoya, coordinadora técnica.

Publicaciones técnicas en revistas indexadas en el JCR

- Díaz-Bello, D., Vargas-Salgado, C., Águila-León, J., & Lara-Vargas, F. (2023). Methodology to Estimate the Impact of the DC to AC Power Ratio, Azimuth, and Slope on Clipping Losses of Solar Photovoltaic Inverters: Application to a PV System Located in Valencia Spain. Sustainability, 15(3), 2797. https://doi.org/10.3390/su15032797

  Aportes: Revisión de redacción y apoyo en la presentación de la información.

- Aguila-Leon, J., Vargas-Salgado, C., Chiñas-Palacios, C., & Díaz-Bello, D. (2022). Solar Photovoltaic Maximum Power Point Tracking Controller Optimization using Grey Wolf Optimizer: A Performance Comparison Between Bio-inspired and Traditional Algorithms. Expert Systems with Applications, 118700. https://doi.org/10.1016/j.eswa.2022.118700

  Aportes: Modelado del convertidor de potencia, controlador, sistema FV, integración de algoritmos, simulación, evaluación y análisis de resultados. Redacción.

- Aguila-Leon, J., Vargas-Salgado, C., Chiñas-Palacios, C., & Díaz-Bello, D. (2022). Energy management model for a standalone hybrid microgrid through a particle Swarm optimization and artificial neural networks approach. Energy Conversion and Management, 267, 115920. https://doi.org/10.1016/j.enconman.2022.115920

  Aportes: Modelado de los sistemas de la microrred, modelado de redes neuronales artificiales, integración de algoritmos, simulación, evaluación y análisis de resultados. Redacción.

- Vargas-Salgado, C., Águila-León, J., Alfonso-Solar, D., & Malmquist, A. (2022). Simulations and experimental study to compare the behavior of a genset running on gasoline or syngas for small scale power generation. Energy, 244, 122633. https://doi.org/10.1016/j.energy.2021.122633

  Aportes: Pruebas simuladas de química de las combustiones utilizando ChemkinPro. Redacción.

- Chiñas-Palacios, C., Vargas-Salgado, C., Aguila-Leon, J., & Hurtado-Pérez, E. (2021). A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid. *Energy Conversion and Management*, 232, 113896. https://doi.org/https://doi.org/10.1016/j.enconman.2021.113896

  Aportes: Arquitectura de redes neuronales, integración de algoritmos, simulación y redacción.

- J. Aguila-Leon, C. Chiñas-Palacios, C. Vargas-Salgado, E. Hurtado-Perez, E.X.M. "Particle Swarm Optimization, Genetic Algorithm and Grey Wolf Optimizer Algorithms Performance Comparative for a DC-DC Boost Converter PID Controller", *Advances in Science, Technology and Engineering Systems Journal*, vol. 6, no. 1, pp. 619-625 (2021). http://dx.doi.org/10.25046/aj060167

  Aportes: Modelado del convertidor de potencia, controlador, modelado de controlador, integración de algoritmos, simulación, evaluación y análisis de resultados. Redacción.

- Aguila-Leon, J., Chiñas-Palacios, C., Garcia, E. X. M., & Vargas-Salgado, C. (2020). A multimicrogrid energy management model implementing an evolutionary game-theoretic approach. *International Transactions on Electrical Energy Systems*, 30(11). https://doi.org/10.1002/2050-7038.12617

  Aportes: Modelado de las microrredes, metodología, integración de algoritmos, simulación, evaluación y análisis de resultados. Redacción.

- Vargas-Salgado, C., Aguila-Leon, J., Chiñas-Palacios, C., & Hurtado-Perez, E. (2019). Low-cost web-based Supervisory Control and Data Acquisition System for a microgrid testbed: A case study in design and implementation for academic and research applications. *Elsevier Heliyon*, 5(9), e02474. https://doi.org/10.1016/j.heliyon.2019.e02474

  Aportes: Programación del PLC, pruebas experimentales, redacción.

Publicaciones técnicas en revistas indexadas en otras bases de datos

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Dirección y asesoramiento de trabajos de tesis y titulación

Codirector de tesis de pregrado:

Esteban Mercado-Mendoza (2019). Intercambiador de cargas eléctricas: propuesta de bajo costo. Universidad de Guadalajara.

Director de tesis de pregrado:

Rodrigo Amaya-Solano (2019). Generación eléctrica por medio de sistemas fotovoltaicos empleando seguidores solares. Universidad de Guadalajara

Asesor de tesis de pregrado:

Fernando Soto-García (2022). Análisis del recurso eólico para la implementación de un aerogenerador de eje vertical en el Centro Universitario de Tonalá. Universidad de Guadalajara.

Talleres, cursos y ponencias

Curso Neural Networks (2021). Talento Altamente Especializado, duración 60 horas. Instituto Jalisciense de Tecnologías de la Información A.C.

Inteligencia Artificial: presente y futuro, un panorama general (2019). Jornadas de la Ciencia. Universidad de Guadalajara.

Algoritmos bio-inspirados para aplicaciones en electrónica de potencia (2020). Jornada Técnica de Crecimiento Personal y Profesional. Universidad Católica de Santiago de Guayaquil.

Redes neuronal artificiales optimizadas para el modelado de sistemas complejos y su aplicación en la generación eléctrica (2022). Escuela Superior Politécnica del Litoral.

Premios, distinciones y otras actividades

Desde el mes de enero de 2023 he obtenido la distinción como miembro del Sistema Nacional de Investigadores (SNI) por parte de Consejo Nacional de Ciencia y Tecnología de México, obteniendo el título de investigador del SNI nivel 1.

Premio a la mejor presentación el 13 de noviembre del año 2020 en la 8th International Conference on Innovation, Documentation and Teaching Technologies (INNODOCT), Valencia, España, por el trabajo "Arduino Based Smart Power Meter: A Low-cost Approach for Academic and Research Applications"

Premio 1er lugar en el Concurso de Ética del 1er. Taller de Líderes Estudiantiles organizado por el IEEE Sección Guadalajara el día 9 y 10 de agosto de 2019 en Guadalajara, México.

En el año 2017 participe como mentor en tutorías de servicio social para el programa Hult Prize Leading a Generation to Change the World con el objetivo de apoyar jóvenes con el desarrollo de sus ideas de impacto social e innovación. En el año 2019 participé como expositor en el evento "Maker Faire Jalisco" organizado por el Centro Regional para la Calidad Empresarial (CReCE), donde se dieron a conocer iniciativas de emprendimiento y creación de redes de contactos para el fortalecimiento de la comunidad de innovación.

Formo parte del comité tutorial que desde 2020 a la fecha ha dado tutorías a alumnos de nivel universitario estudiantes de Ingeniería en Energía y de Nanotecnología en la Universidad de Guadalajara, para el fortalecimiento de la comunidad universitaria.

En el año 2021 participé como mentor en el programa de mentorías la segunda edición del curso de verano Experiencia a Distancia para Jóvenes Ingenieros y Científicos "Remote Experience for Young Engineers and Scientists (REYES)" organizado por la institución Old Dominion University, donde di mentoría a jóvenes de la comunidad internacional con interés en las STEM con el objeto de brindar asesorías metodológicas a vocaciones tempranas.