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Bio-Inspired Algorithms and Artificial Neural Networks Applied to Smart Load Management Systems to Optimize Energy Usage

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Valencia, Spain

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To my parents, siblings, teachers, tutors, co-workers, and friends

For their love, support, and unconditional affection during all stages of my development as a human being. Their advice, experiences, friendship, and knowledge have been very valuable to me, as they have helped me to give the best of me throughout my entire life.

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ABSTRACT

Energy, communication, and computing are critical components of modern society, providing the foundation for technological development and economic growth. The close interrelation between these pillars has become increasingly apparent in recent years, as computing and data analysis advances have enabled new energy management and sustainability approaches. In this context, efficient energy usage has become a key focus for researchers, policymakers, and businesses alike. By harnessing the power of computing and machine learning (ML) techniques, it is possible to highlight the challenges of securing energy systems and optimizing energy usage, leading to the need for advanced techniques such as bio-inspired algorithms and neural networks.

This doctoral thesis aims to analyse load consumption and demand management programs and strategies in the current energy landscape. The central core presents an study on integrating bio-inspired algorithms, such as particle swarm optimization (PSO) and artificial neural networks (ANN) models in load management systems to meet load management challenges and use energy efficiently and securely.

The main body of this thesis comprises three scientific publications, each corresponding to a distinct stage within the overarching research framework of this study: the first stage covers the proposal of a low-cost architecture in energy systems introducing a cost-effective web-based SCADA system that was over 80% cheaper than a similar solution. The proposed low-cost architecture, tailored for microgrid testbeds, offers real-time monitoring, remote accessibility, and user-friendly control for academic and research applications. The second stage combined a cascade hybrid Particle Swarm Optimization (PSO) with feed-forward neural networks to accurately forecast and optimize energy demand in an AC microgrid, notably enhancing the integration of renewable energy sources like biomass gasification. The results showed that the proposed PSO-ANN model performs 23.2% better in terms of MSE than Feedforward Backpropagation (FF-BP) and Cascade forward propagation (CF-P) ANN models. The third and final stage focused on a smart load management system fortified with hybrid cryptography to ensure protected communication and data privacy, thereby effectively addressing energy security challenges in residential settings. Results showed that the proposed Security Residential

System Load Management (SRS-LM) model was 37% better in performance (power cost, power utilization, computational time) and with a 60% peak load reduction compared to a Universal Smart Energy Meter (USEM) model.

RESUMEN

La energía, la comunicación y la informática son componentes fundamentales de la sociedad moderna, ya que sientan las bases para el desarrollo tecnológico y el crecimiento económico. La estrecha interrelación entre estos pilares se ha hecho cada vez más evidente en los últimos años, a medida que los avances en computación y análisis de datos han permitido nuevos enfoques de gestión y sostenibilidad de la energía. En este contexto, el uso eficiente de la energía se ha convertido en un objetivo clave para los investigadores, los responsables políticos y las empresas por igual. Al aprovechar el poder de las técnicas informáticas y de aprendizaje automático (ML), es posible destacar los desafíos de asegurar los sistemas de energía y optimizar el uso de la energía, lo que lleva a la necesidad de técnicas avanzadas como algoritmos bio-inspirados y redes neuronales.

Esta tesis doctoral tiene como objetivo analizar los programas y estrategias de gestión de la carga, el consumo y la demanda en el panorama energético actual. El núcleo central presenta un estudio exhaustivo sobre la integración de algoritmos bio-inspirados, como la optimización de enjambres de partículas (PSO) y los modelos de redes neuronales artificiales (ANN) en los sistemas de gestión de la carga para hacer frente a los retos de la gestión de la carga y utilizar la energía de forma eficiente y segura.

El cuerpo principal de esta tesis comprende tres publicaciones científicas, cada una de las cuales corresponde a una etapa distinta dentro del marco general de investigación de este estudio: la primera etapa propone un sistema de monitorización de bajo coste para aplicaciones energéticas que introduce un sistema SCADA basado en web rentable que era un del 80% más barato que una solución similar. La arquitectura de bajo coste propuesta, diseñada para bancos de pruebas de microrredes, ofrece monitorización en tiempo real, accesibilidad remota y control fácil de usar para aplicaciones académicas y de investigación. La segunda etapa combina la optimización híbrida de enjambre de partículas (PSO) en cascada con redes neuronales feed-forward para pronosticar y optimizar con precisión la demanda de energía en una microrred en AC, mejorando la integración de fuentes de energía renovables como gasificación de biomasa. Los resultados muestran que el modelo PSO-ANN propuesto tiene un rendimiento un 23,2% mejor en términos de MSE que los modelos de RNA de retropropagación feed-forward

(FF-BP) y propagación directa en cascada (CF-P). La tercera y última etapa se centró en un sistema inteligente de gestión de la carga reforzado con criptografía híbrida para garantizar la comunicación protegida y la privacidad de los datos, abordando así de manera efectiva los desafíos de seguridad energética en entornos residenciales. Los resultados mostraron que el modelo propuesto de Gestión de Carga aplicado a Sistemas Residenciales de Seguridad (SRS-LM) fue un 37% mejor en rendimiento (costo de energía, utilización de energía, tiempo computacional) y con una reducción de carga máxima del 60% en comparación con un modelo de Medidor de Energía Inteligente Universal (USEM).

RESUM

L'energia, la comunicació i la informàtica són components fonamentals de la societat moderna, ja que establixen les bases per al desenvolupament tecnològic i el creixement econòmic. L'estreta interrelació entre estos pilars s'ha fet cada vegada més evident en els últims anys, a mesura que els avanços en computació i anàlisi de dades han permés nous enfocaments de gestió i sostenibilitat de l'energia. En este context, l'ús eficient de l'energia s'ha convertit en un objectiu clau per als investigadors, els responsables polítics i les empreses per igual. En aprofitar el poder de les tècniques informàtiques i d'aprenentatge automàtic (ML), és possible destacar els desafiaments d'assegurar els sistemes d'energia i optimitzar l'ús de l'energia, la qual cosa porta a la necessitat de tècniques avançades com a algorismes bio-inspirats i xarxes neuronals.

Esta tesi doctoral té com a objectiu analitzar els programes i estratègies de gestió de la càrrega, el consum i la demanda en el panorama energètic actual. El nucli central presenta un estudi exhaustiu sobre la integració d'algorismes bio-inspirats, com l'optimització d'eixams de partícules (PSO) i els models de xarxes neuronals artificials (ANN) en els sistemes de gestió de la càrrega per a fer front als reptes de la gestió de la càrrega i utilitzar l'energia de manera eficient i segura.

El cos principal d'esta tesi comprén tres publicacions científiques, cadascuna de les quals correspon a una etapa diferent dins del marc general d'investigació d'este estudi: la primera etapa proposa un sistema de monitoratge de baix cost per a aplicacions energètiques que introduïx un sistema SCADA basat en web rendible que era un del 80% més barat que una solució similar. L'arquitectura de baix cost proposada, dissenyada per a bancs de proves de microxarxes, oferix monitoratge en temps real, accessibilitat remota i control fàcil d'usar per a aplicacions acadèmiques i d'investigació. La segona etapa combina l'optimització híbrida d'eixam de partícules (PSO) en cascada amb xarxes neuronals feed-forward per a pronosticar i optimitzar amb precisió la demanda d'energia en una microxarxa en AC, millorant la integració de fonts d'energia renovables com a gasificació de biomassa. Els resultats mostren que el model PSO-ANN proposat té un rendiment un 23,2% millor en termes de MSE que els models d'RNA de retropropagació feed-forward (FF-BP) i propagació directa en cascada (CF-P). La tercera i última etapa

es va centrar en un sistema intel·ligent de gestió de la càrrega reforçat amb criptografia híbrida per a garantir la comunicació protegida i la privacitat de les dades, abordant així de manera efectiva els desafiaments de seguretat energètica en entorns residencials. Els resultats van mostrar que el model proposat de Gestió de Càrrega aplicat a Sistemes Residencials de Seguretat (SRS-LM) va ser un 37% millor en rendiment (cost d'energia, utilització d'energia, temps computacional) i amb una reducció de càrrega màxima del 60% en comparació amb un model de Mesurador d'Energia Intel·ligent Universal (USEM).

Contents

List of Figures

List of Tables

Acronyms

ABC	Artificial Bee Colony
AC	Alternating Current
ADC	Analog-Digital Converter
AMI	Advanced Metering Infrastructure
ANFIS	Adaptive Neural Fuzzy Inference System
ANN	Artificial Neural Network
ARWBS	Arduino-Raspberry Pi 3 Wireless Base Station
AWMDC	Arduino Wireless Meteorological Data Collector
AWPM	Arduino Wireless Power Meter
AWSC	Arduino Wireless Switch Controller
BGP	Biomass Gasification Plant
CF-P	Cascade Forward Propagation
CNN	Convolutional Neural Network
CONACYT	National Council of Humanities Science and Technology
DB	Database
DR	Demand Response
DSM	Demand Side Management
EBPGS	Energy Backup Power Generation Systems
ECC	Elliptic Curve Cryptography
EMS	Energy Management System
ESS	Energy Storage Systems
FF-BP	Feedforward Backpropagation
FIS	Fuzzy Inference System
FL	Fuzzy Logic
GA	Genetic Algorithm
HNN	Hopfield Neural Network
HRES	Hybrid Renewable Energy System
HTML	HyperText Markup Language
ICE	Internal Combustion Engine
IdM	Identity Management
INSL	Interruptible and Non-Schedulable Loads
IoT	Internet of Things
JCR	Journal Citation Report
k-NN	k-Nearest Neighbor
LabDER-UPV	Laboratory Distributed Energy Resources at Universitat Politecnica de Valencia

LC-SCADA	Low-cost Supervisory Control And Data Acquisition
LHV	Lower Heating Value
LMS	Load Management System
MAC	Message Authentication Code
MC	Markov Chain
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean Square Error
MySQL DB	MyStrcutred Query Language Database
NILM	Non-Intrusive Load Monitoring
NINSL	Non-Interruptible and Non-Schedulable Loads
PhD	Philosophiae Doctor
PHP	Hypertext Preprocessor
PSO	Particle Swarm Optimization
PV	Photovoltaic
QoE	Quality of Experience
RBF	Radial Basis Function
RES	Renewable Energy Source
RTU	Remote Terminal Unit
SCADA	Supervisory Control And Data Acquisition
SG	Smart Grid
SH	Smart Home
SL	Schedulable Loads
SM	Smart Meter
SPI	Serial Peripheral Interface
SRS-LM	Smart Residential Security assisted Load Management
TCP/IP	Transmission Control Protocol / Internet Protocol
TEG	Thermoelectric Generator
UPV	Universitat Politecnica de Valencia
USEM	Universal Smart Energy Meter
WTG	Wind Turbine Generator

Chapter 1. Introduction

This thesis was written under the modality of journal compilation publishing. It covers the key findings and main results of four years of research reflected in three scientific papers published in journals indexed in the Journal Citation 1Report (JCR). This thesis follows four chapters, where the first describes the research background, state-of-art, motivation, methodology, and main objectives of this work. The second chapter includes the author's publications, the third chapter mentions the summary conclusions of all the scientific papers and discusses future work, and the final chapter remarks the complementary activities during the development of this work. The structure of the thesis contains a logical order starting with the infrastructure design of the microgrid system to gather data from all renewable energy resources to implement a model to optimize the energy generation, distribution network, and securing/protecting data; all of this by using machine learning (ML) techniques and optimization algorithms.

1.1 BACKGROUND

The transition towards a sustainable energy future has brought significant attention to demand response programs that incentivize energy consumers to modify their electricity consumption patterns in response to energy supply or price changes. Demand response programs have effectively reduced peak demand, improved energy efficiency, and enhanced grid reliability and stability [1], [2]. Machine learning techniques have been increasingly applied in demand response programs to develop predictive models that can accurately forecast energy consumption patterns and optimize demand response strategies [3], [4]. Low-cost energy systems, including microgrids and off-grid systems, have also emerged as a promising solution to address energy poverty and promote sustainable energy access in remote and rural areas [5], [6]. Bio-inspired algorithms have been proposed as a computational tool to optimize system design, control, and operation to improve the performance and affordability of these systems [7], [8]. These algorithms simulate natural processes such as evolution, swarm intelligence, and neural networks to solve complex optimization problems and achieve better energy efficiency and cost-effectiveness[9].

Microgrids are complex systems with multiple distributed energy resources, such as solar panels, wind turbines [10], and energy storage devices, that must be controlled and managed efficiently. The efficient operation of microgrids requires the optimization of various parameters, including power generation, energy storage, and load management, to ensure that the energy demand is met while minimizing energy costs and reducing greenhouse gas emissions.

Demand response, machine learning techniques, low-cost energy systems, bio-inspired algorithms, and energy efficiency are interconnected research topics that can contribute to developing a sustainable and reliable energy system environment. By leveraging advanced technologies and interdisciplinary approaches, researchers and practitioners can overcome technical, economic, and social barriers to promote sustainable energy access and reduce greenhouse gas emissions.

A Load Management System (LMS) can reduce energy costs and improve the microgrid's reliability by balancing supply and demand [11]. Similarly, a study by [12] suggests that demand response (DR) techniques can effectively reduce peak demand and mitigate the need for additional energy generation capacity.

The effectiveness of LMS and DR can be improved by using advanced technologies such as machine learning algorithms and smart grid communication systems. For example, a study by [13] found that machine learning algorithms can optimize the energy consumption of loads in a microgrid, improving the efficiency of the LMS. Similarly, a study by [14] suggests that smart grid communication systems can improve DR's effectiveness by providing real-time information on energy demand and supply.

Implementing LMS and DR can have significant economic and environmental benefits, such as reducing energy costs and greenhouse gas emissions and improving the overall energy efficiency of the microgrid. A study developed by [15] found that implementing LMS and DR in a microgrid can reduce the peak load by up to 30%, resulting in significant cost savings and emissions reductions. Similarly, a study developed by [16] suggests that DR can help improve microgrids' overall energy efficiency by reducing energy waste during peak periods. Some of the key findings include:

- LMS can reduce energy costs and improve the microgrids' reliability by balancing supply and demand.

- DR can effectively reduce peak demand and mitigate the need for additional energy generation capacity.

- The effectiveness of LMS and DR can be improved by using advanced technologies such as machine learning algorithms and smart grid communication systems.

- Implementing LMS and DR can have significant economic and environmental benefits, such as reducing energy costs greenhouse gas emissions and improving the overall energy efficiency of the microgrid.

LMS and DR are two important strategies for efficient energy management in microgrids. LMS refers to the process of managing the energy consumption of the connected loads in a microgrid to balance supply and demand. DR refers to the process of reducing the demand for electricity during peak periods by adjusting the energy consumption of the loads [17]. Several studies have examined the use of LMS and DR in microgrids.

1.1.1 Designing low-cost energy systems for microgrids

Microgrids have emerged as a promising solution to address the challenges of reliable and sustainable energy access, especially in remote and rural areas. Microgrids can also provide benefits such as reduced energy costs, improved energy security, and reduced greenhouse gas emissions. However, the deployment and management of microgrids require advanced control and monitoring systems to ensure their efficient operation and reliable performance.

One of the critical components of microgrid control systems is Supervisory Control and Data Acquisition (SCADA) systems, which are used for real-time monitoring and control of microgrid components and performance. Traditional SCADA systems are often expensive, complex, and closed-source, which limits their adoption in academic and research applications. To overcome these limitations, researchers and engineers have been exploring the development of low-cost, open-source, and web-based SCADA systems for microgrids.

1.1.2 Bio-inspired algorithms to support energy efficiency in microgrids

Bio-inspired algorithms, also known as nature-inspired algorithms, are computational methods that imitate the behaviour and principles observed in natural systems such as animals, plants, and ecosystems. These algorithms are becoming increasingly popular in the field of energy management and have shown great potential in optimizing the performance of microgrids.

Bio-inspired algorithms can provide an effective and efficient approach to optimizing the performance of microgrids. These algorithms use principles such as evolution, swarm intelligence, and neural networks to optimize the energy management of microgrids. For example, genetic algorithms can be used to optimize the scheduling of energy resources, particle swarm optimization can be used to optimize the control of energy storage devices, and artificial neural networks can be used to predict energy demand and optimize energy consumption schedules.

Applying bio-inspired algorithms in microgrid energy management can have significant benefits, including improved energy efficiency, reduced energy costs, and enhanced grid stability. These algorithms can also provide a scalable and adaptable approach to microgrid optimization, which can be particularly beneficial for microgrids in remote or rural areas. They offer a promising approach to support energy efficiency in microgrids. By leveraging principles from nature, these algorithms can optimize the performance of microgrids, leading to reduced energy costs, improved energy efficiency, and enhanced grid stability.

1.1.3 Integration of machine learning techniques in load management systems

Load management systems (LMS) are an important tool for optimizing the operation of microgrids and reducing energy costs. Machine learning techniques, such as artificial neural networks, genetic algorithms, and support vector machines, have shown great potential for improving the performance of LMS.

One of the main advantages of using machine learning techniques in LMS is the ability to predict and control energy demand in real-time. These techniques can be used to model the behaviour of energy consumers, predict future energy demand, and optimize energy usage based on the predicted demand. This can lead to more efficient use of energy resources and a reduction in energy costs.

Integrating machine learning techniques in load management systems can provide an effective and efficient approach to energy management in microgrids. By predicting and optimizing energy demand in real-time, these techniques can lead to reduced energy costs, increased energy efficiency, and improved grid stability.

Overall, the integration of machine learning techniques in load management systems can significantly improve the energy efficiency and reliability of microgrids. These techniques can provide an effective approach to predicting energy demand, optimizing the operation of DERs, and reducing energy costs and CO2 emissions.

1.2 MOTIVATION

This thesis focuses on designing and implementing energy management models to optimize energy use by combining bio-inspired algorithms and artificial neural networks with a focus on energy and load management systems. Load management systems and demand response programs are essential for balancing energy supply and demand and reducing energy costs in electricity grids. Load management systems involve the real-time monitoring and control of energy consumption, particularly during peak periods, to ensure that energy supply meets demand. Demand response programs aim to encourage consumers to adjust their energy usage patterns during peak demand periods, typically through incentives or penalties.

Machine learning techniques have shown significant potential in improving the effectiveness and efficiency of load management systems and demand response programs. These techniques can analyse large amounts of data from smart meters, weather sensors, and other sources to identify patterns in energy consumption and predict future demand. Machine learning algorithms can also be used to optimize energy consumption schedules and identify opportunities for energy savings.

The application of machine learning techniques in load management systems and demand response programs can have significant benefits, including reduced energy costs, improved energy efficiency, and enhanced grid stability. Machine learning can enable load management systems to respond more quickly and accurately to changes in energy supply and demand, leading to more efficient use of energy resources. It can also help to reduce energy consumption during peak periods, reducing the need for expensive peaking power plants and minimizing the risk of blackouts.

In summary, load management systems and demand response programs can benefit electricity grids significantly, and machine learning techniques can enhance their effectiveness and efficiency. By leveraging machine learning algorithms, energy providers can optimize energy consumption schedules, reduce energy costs, and improve the reliability and stability of the electricity grid.

1.3 STRUCTURE

The modality in which this thesis focuses is by journal compilation publishing. It consists of three scientific papers published in JCR journals. This document is structured in four chapters.

Chapter one presents the state of the art of data acquisition systems for energy management in microgrids, demand response and optimization algorithms applied to renewable energy systems scenarios.

Chapter two describes the three scientific publications in detail. The first explains the low-cost data acquisition system architecture of an experimental microgrid. The second one addresses the energy management model using artificial neural networks with particle swarm optimization applied to a gasification plant considering the design of the acquisition and monitoring system architecture, and the energy management model using neural networks and metaheuristic algorithms applied to a gasification plant are mentioned. The third one explains the proposal of a home load management model. A novel hybrid cryptography as an improvement contribution to the proposed management system is described.

Chapter three mentions the discussion and conclusions of the three JCR papers, and the future work of each one is explained.

Chapter four shows other scientific publications and research activities throughout the current thesis period.

1.4 METHODOLOGY

This thesis presents a methodology that integrates and combines various metaheuristic algorithms for managing energy demand and load control in environments where electricity generation is provided by microgrids, and domestic consumption patterns are considered. Hence, the methodology of this study is divided into three stages (as shown in Figure 1) which are described below:

1. Architecture and data acquisition systems using smart meters for a generation microgrid based on renewable energies.

    - A full review of the state-of-the-art data acquisition techniques considering low-cost devices in hybrid renewable energy systems was completed at this stage. Several studies were collected and analysed to identify best microgrid scenarios and trends for energy generation and load consumption developments in this field of research.

2. Integrating artificial neural networks and optimization algorithms for energy management in a microgrid using a gasifier.

    - This stage focused on two ANN models (Cascade Forward and Feedforward Propagation) integrating a bio-inspired algorithm (Particle Swarm Optimization). Several tests were simulated in Matlab to prove the best result for power generation of a gasification plant.

3. Design and implementation of a Load Management System model based on Demand-Response techniques alongside machine learning algorithms.

    - The final stage of this investigation concluded with the implementation the proposed model integrating algorithms and neural networks. Hybridization with specific algorithms was tested in a neighbourhood's virtual environment with Smart Homes, considering historical load consumption data. Results were evaluated in terms of power usage, power cost, computational cost, etc.

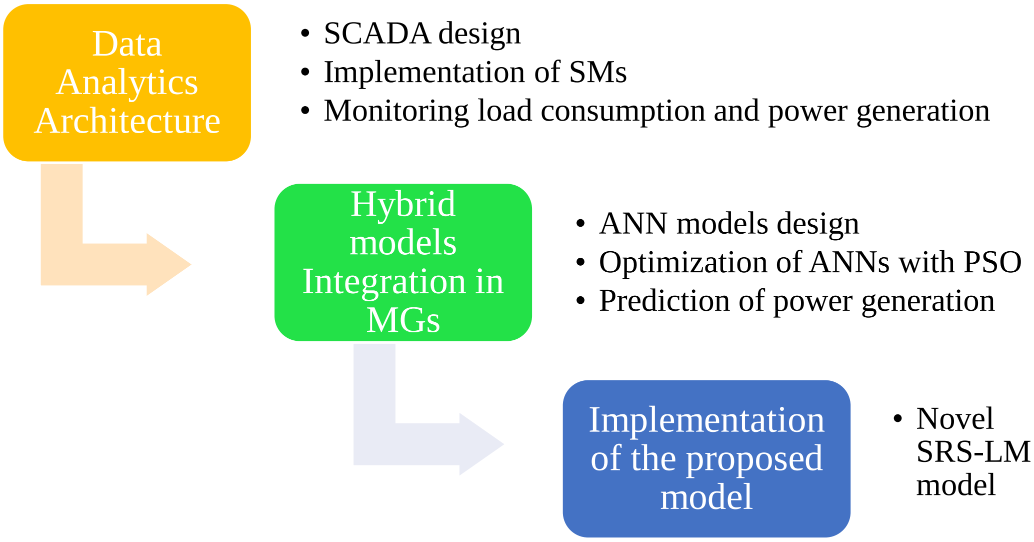

Figure 1 Research methodology stages in this study. Source: own elaboration.

1.5 OBJECTIVES

This thesis aims to design, develop, integrate, and implement a Load Management System for reducing energy consumption based on machine learning techniques and bio-inspired algorithms in microgrids/smart homes. However, as mentioned in the methodology section, every stage has a list of unique objectives to achieve the main purpose and validate the proposed models described in each chapter of this thesis. For each state, a paper was developed. The goals of each stage are explained below:

1.5.1 Low-cost monitoring systems for supervision of energy consumption

For the initial stage, the system needs to collect data and microgrid system's data to monitor the power generation coming from the renewable sources and store them in a local and cloud-based database. The main objectives are:

- To identify and analyse energy consumption patterns using of low-cost monitoring systems within the microgrid to develop strategies for reducing energy usage in these areas and optimizing energy efficiency. This will detect anomalies in the energy consumption that helps to identify unusual spikes or drops in energy usage. Analysing energy consumption patterns may indicate issues with the energy system or equipment to prevent energy waste.

- To develop strategies for optimizing energy usage, such as adjusting energy usage during off-peak hours or implementing energy-saving measures by applying any demand-response techniques.

1.5.2 Artificial neural network model for covering energy demand

In this stage the system's architecture must be collecting data to propose a model to cover several objectives mentioned above:

- To design a hybrid ANN model with PSO algorithm to predict the energy demand in the microgrid accurately to minimize waste and reducing cost of energy production.

1.5.3 Machine Learning techniques in a Load Management System model.

For this specific and final stage, the load management system model should include machine learning techniques to operate the whole system. The three main objectives of the model are:

- To optimize the distribution of residential energy consumption using a Hopfield Neural Network, predict the state of loads in homes using Markov Chains, reduce the cost of the electricity bill through Fuzzy logic, achieve a high level of security in the data network using a hybrid encryption algorithm Blowfish, and the Elliptic Curve Cryptography (ECC) method.

- To develop a demand management model (DSM – Demand-Side Management) by integrating optimization algorithms into energy management systems (Energy Management System) and data security in smart homes (Smart Homes).

- To develop energy demand management models for energy savings in residential homes based on metaheuristic optimization algorithms that incorporate the demand response technique to reduce peak demand in periods of increased consumption.

1.6 Contributions

This thesis proposes a new methodology to the demand-response in residential energy management as a solution to the consumption of fossil sources in power generation, high energy prices in the hours of highest energy consumption (peak hours), or sudden changes in load. Likewise, the present work contributes to developing energy management algorithms based on metaheuristic optimization and machine learning techniques in the residential sector, emphasizing the novel methods inspired by the behaviour of different species in nature, the Particle Swarm Optimization – PSO.

On the other hand, the present work directly impacts energy efficiency in the home, by providing the user with a tool for classification, or categorization, of the loads of appliances and devices that are linked to the information of the SM and that allow the integration of hybrid systems of renewable electricity generation in homes or any residential area, along with an intelligent energy manager system that significantly improves the quality of the electricity grid by reducing peak demand with the inclusion of environmentally friendly technology.

The contributions of every single paper of the entire work have been published in international indexed journals as mentioned below:

[1] 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". Heliyon, 5(9). https://doi.org/10.1016/j.heliyon.2019.e02474.

- The paper described the infrastructure design of a web-based Supervisory Control and Data Acquisition (SCADA) system for a microgrid testbed where the SCADA was implemented considering open-source software and low-cost hardware, making it an affordable solution for academic and research applications. The SCADA system was designed to monitor and control the different components of the microgrid testbed, such as the solar panels, battery, and loads. A web-based interface was previously designed to allow remote access to the SCADA system, making it easy to monitor and control the microgrid from anywhere with an internet connection.

- The paper includes a case study of the SCADA system in a microgrid testbed at the UPV where the installation process is described, and tests were implemented on how the SCADA system can successfully monitor and control the microgrid.

- In general, the paper demonstrated that a low-cost web-based SCADA system can effectively monitor and control microgrids in academic and research settings where the proposed SCADA system can be adapted for any microgrid applications.

[2] Chiñas-Palacios, C., Vargas-Salgado, C., Aguila-Leon, J., and 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, vol. 232, no. 113896. https://doi.org/10.1016/j.enconman.2021.113896.

- The paper proposed a cascade hybrid Particle Swarm Optimization (PSO) feed-forward neural network model to predict the output power of a biomass gasification plant. The novel model aimed to use the predicted power output to cover an AC microgrid's energy demand. Such model includes a wind turbine, a photovoltaic array, and an energy storage system.

- The proposed model was trained with real data coming from the biomass gasification plant at the UPV. The results were compared with those obtained from other prediction models. The results showed that the proposed model outperforms other models.

- The paper also includes a case study in which the proposed model predicted the biomass gasification plant's output power and covers the AC microgrid's energy demand. Thus, the proposed model can effectively manage the energy supply and demand of the microgrid, reducing the need for additional energy sources and improving the system's overall energy efficiency.

- As a result, the proposed cascade hybrid PSO feed-forward neural network model can be an effective solution for predicting the output power of a biomass gasification plant and managing the energy supply and demand of an AC microgrid.

[3] C. Chiñas-Palacios, J. Aguila-Leon, C. Vargas-Salgado, E. X. M. Garcia, J. Sotelo-Castañon, and E. Hurtado-Perez, "A smart residential security assisted load management system using hybrid cryptography," *Sustain. Comput. Informatics Syst.*, vol. 32, no. 100611, 2021, https://doi.org/10.1016/j.suscom.2021.100611.

- The paper proposed a smart residential security-assisted load management system that uses hybrid cryptography to secure communication between the system components. The system managed the electricity load in a residential setting by controlling the devices connected to the grid and balancing the energy demand with the available energy supply.
- The components of the system included a load management controller, a secure communication module, and a smart device management module. Also, a hybrid cryptography-based security mechanism was proposed to protect the communication between these components. The paper includes a case study of implementing the proposed system in a residential setting. The system can effectively manage the electricity load while maintaining communication security between the system components.
- Overall, the proposed smart residential security-assisted load management system using hybrid cryptography can be an effective solution for managing the electricity load in residential settings while ensuring the system's security. Furthermore, the system can be adapted for applications considering other scenarios and settings, such as commercial or industrial applications.

This research addresses the problem of energy management and data security in microgrids and smart homes in a novel way by proposing the integration of optimization algorithms into the grid to improve energy generation and consumption efficiently. A literature review in Table 1 describes the current situation of the low-cost energy systems in microgrids alongside bio-inspired algorithms to support energy efficiency and the integration of advanced ML techniques for load management systems regarding demand response.

Table 1 Comparative results of the three stages considered for this thesis.

Literature Work	Problems Considerations	Proposed Model Solution
Stage 1. Designing Low-Cost Energy Systems for Microgrids		
Development of a Web-Based Real-time Energy Monitoring System for Campus University (Dahlan et al., 2016)	The monitoring system considered by the authors was a remote web-based SCADA but only displayed real power consumption.	Electrical parameters such as voltage, current, frequency, energy, and load consumption were included in the proposed model.
Stage 2. Bio-inspired Algorithms to Support Energy Efficiency in Microgrids		
Smart Sensing of Loads in an Extra Low Voltage DC Pico-grid using Machine Learning Techniques [18]	Clustering is only done once. Load changes are not updated. Classification based on clustered data is not effective.	Load is determined in the Markov chain model, which efficiently predicts future states. Dynamically updates the state of charge according to the energy consumption in the microgrid.
Design and implementation of low–cost universal smart energy meter with demand-side load management [19]	Emergency load is initially stored on the central server; in some cases, it cannot handle the load demand. If more than one consumer demands electricity, managing the load becomes complex.	Household appliances are classified into three types, according to the load consumption. Depending on the electricity grid's usage limit, the consumer's appliances are monitored in case of an overload.
Stage 3. Integration of Machine Learning Techniques in Load Management Systems		
A novel low-cost smart energy meter based on IoT for developing countries' micro grids [20]	An app for Android devices is equipped to update power failures and payments; It is essential to be online or logged in. Stolen mobile device causes many security issues. Requires improved security to ensure privacy and authentication.	In the proposed work, the information on the behaviour of the IoT device is considered. Therefore, even if a mobile device is stolen, the third party cannot decrypt the data because only after successful authentication will the remaining part of the key be granted. The smart meter is authenticated, and the measurements are securely delivered to the user.
Design and Development of an Adaptive Fuzzy Control system for Power Management in Residential Smart Grid Using Bat Algorithm [21]	The energy consumption of each user is predicted using the authors' algorithm; however, energy management based on demand response was not achieved.	Energy management is achieved by controlling appliances within the residential area.
A Novel Approach for Detecting and Mitigating the energy Theft Issues in the Smart Metering Infrastructure [22]	Vulnerable to physical manipulation (electromagnetic interference gives erroneous readings). The measured values are part of a function where the values are not reviewed.	The smart energy meter is authenticated in the proposed work, so authorized smart meters can only share information about the measured values.

* Source: Own elaboration.

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Chapter 2. Scientific publications

This chapter presents three scientific publications that address the architecture of low-cost power systems, the design of energy management models and the integration of optimization algorithms. The papers were published in chronological order, starting from the first stage of the methodology (data extraction and loading into a cloud database), following the second stage (working with bio-inspired algorithms and neural networks to test the system's power generation), and the third and last stage (covering the implementation of the proposed energy and load management model).

The first publication, entitled "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" focuses on the design of a low-cost web-based Supervisory Control and Data Acquisition (SCADA) system for a microgrid testbed. The SCADA system was designed to monitor and control the different components of the microgrid testbed, such as the solar panels, battery, and loads. This paper covers the first stage that is gathering data coming from the renewable energy sources and creating the database to store all systems' information.

The second publication, entitled "A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid" introduces a hybrid model combining PSO feed-forward with artificial neural networks (ANN) models to predict the output power of a biomass gasification plant, according to energy and biomass required. Results showed that the proposed model could be an effective solution for predicting the output power of a biomass gasification plant and managing the energy supply and demand of an AC microgrid.

The final and third publication, "A smart residential security assisted load management system using hybrid cryptography" proposes a smart residential security-assisted load management system that uses hybrid cryptography to secure communication between the system components. The system was designed to manage the electricity load in a residential setting by controlling the devices connected to the grid and balancing the energy demand with the available energy supply.

2.1 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

Vargas-Salgado, C., Aguila-Leon, J., Chiñas-Palacios, C., & Hurtado-Perez, E. (2019)

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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

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ABSTRACT

This paper presents the design and implementation of a low-cost Supervisory Control and Data Acquisition system based on a Web interface to be applied to a Hybrid Renewable Energy System (HRES) microgrid. This development will provide a reliable and low-cost control and data acquisition systems for the Renewable Energy Laboratory at Universitat Politècnica de València (LabDER-UPV) in Spain, oriented to the research on microgrid stability and energy generation. The developed low-cost SCADA operates on a microgrid that incorporates a photovoltaic array, a wind turbine, a biomass gasification plant and a battery bank as an energy storage system. Sensors and power meters for electrical parameters, such as voltage, current, frequency, power factor, power generation, and energy consumption, were processed digitally and integrated into Arduino-based devices. A master device on a Raspberry-PI board was set up to send all this information to a local database (DB), and a MySQL Web-DB linked to a Web SCADA interface, programmed in HTML5. The communications protocols include TCP/IP, I2C, SPI, and Serial communication; Arduino-based slave devices communicate with the master Raspberry-PI using NRF24L01 wireless radio frequency transceivers. Finally, a comparison between a standard SCADA against the developed Web-based SCADA system is carried out. The results of the operative tests and the cost comparison of the own-designed developed Web-SCADA system prove its reliability and low-cost, on average an 80% cheaper than a standard brandmark solution, for controlling, monitoring and data logging information, as well as for local and remote operation system when applied to the HRES microgrid testbed.

2.1.1 Abstract

This paper presents the design and implementation of a low-cost Supervisory Control and Data Acquisition system with a Web interface for a Hybrid Renewable Energy System (HRES) microgrid. This work is carried out as an effort to provide a reliable and low-cost testbed for the Renewable Energy Laboratory at Universitat Politècnica de València (LabDER-UPV) in Spain, allowing future research on microgrid stability and energy transactions using an own-designed low-cost solution. The microgrid in which the developed low-cost SCADA operates incorporates a photovoltaic array, a wind turbine, a biomass gasification plant and a battery bank as an energy storage system. Sensors and power meters were processed digitally and integrated into Arduino-based devices to acquire environmental data and electric parameters, such as voltage, current, frequency, power factor, power generation, and energy consumption. A master device on Raspberry-PI development board was set up to send the information acquired into a local database (DB) as well as to a MySQL Web-DB linked to a Web SCADA interface developed and programmed in HTML5. Communications protocols used include TCP/IP, I2C, SPI, and Serial; Arduino-based slave devices communicate over the master Raspberry-PI using NRF24L01 wireless radio frequency transceivers. Finally, a comparison between a standard SCADA against the low-cost developed Web-based SCADA system is carried out. As a result of the operative tests and the cost comparison of the own-designed developed Web-SCADA system proved to be an affordable low-cost system, on average 86% cheaper than a standard brandmark solution for controlling, monitoring and data logging information, as well as for local and remote operation system applied to the HRES microgrid testbed presented.

Keywords: Hybrid Renewable Energy System; Web-based SCADA; remote control and wireless monitoring; cloud computing; Arduino; Raspberry.

Abbreviations

The following abbreviations are used in the manuscript:

AWMDC	Arduino wireless meteorological data collector
AWPM	Arduino wireless power meter
AWSC	Arduino wireless switch controller
HRES	Hybrid Renewable Energy System
LC-SCADA	Low-cost Supervisory Control and Data Acquisition
SCADA	Supervisory Control and Data Acquisition

2.1.2 Introduction and state-of-art

Electricity demand has increased due to the growth of population around the world and conventional grids have evolved into intelligent grids, better known as Smart Grids (SG). Along with the Smart Grids, the use of Renewable Energy Sources has grown in the form of microgrid systems. Besides the penetration of decentralized renewable sources in the grid, as microgrids, the inclusion of Information Technologies in Energy Renewable Systems has grown over the last decade making management of energy, data and communications issues for these systems due to a lack of standardization in the topic [23], [24]. Because microgrid systems are itself an integration of many renewable energy sources and energy storage systems working co-ordinately, a microgrid can be designed following one of two main control topologies: centralized or decentralized. No matter which topology is selected, data flow and communications are essential for any decision-making controller [25], [26]. Common microgrid controllers are often based on Programmable Logic Controllers (PLC) [27], dedicated computers microgrid simulators [28] and microcontroller-based devices[29], [30]. Selection of a proper controller should be addressed accordingly to the microgrid application, financial budget, and security issues. As there is no consensus about which control topology and which controller hardware technology is better, due to application target, there are also many communication protocols available with many different characteristics [31].

In this paper, it is presented the methodology of developing a low-cost SCADA system for an experimental microgrid testbed for academic and research proposes, as well as the results of operational tests and investment for the system implementation. Since the SCADA system is nowadays becoming an essential part of electric power systems, such as microgrids, it is important to consider an accurate testbed development. It is mentioned in [32] that there are five main approaches for testbed developments, shown in Table 2.

Table 2 Testbed development approaches.

Testbed Approach	Fidelity	Repeatability	Accuracy	Safety	Cost-effective	Reliability	Scalability
Physical replication	Excellent	Poor	Moderate	Poor	Poor	Excellent	Poor
Simulated	Low	Moderate	Poor	Excellent	Excellent	Poor	High
Virtual	Moderate	High	Moderate	Excellent	Moderate	Moderate	Moderate
Virtual-Physical	High	High	Excellent	Excellent	High	High	Moderate
Hybrid	High	High	Excellent	High	High	High	Moderate

* Taken from [10].

The low-cost SCADA system developed in this paper is intended to operate over a physical replication of a microgrid, so the fidelity and operative conditions are real. A brandmark SCADA system for a microgrid has poor cost-effectiveness since dataloggers, controllers, sensors and related devices are expensive as they are usually made for industrial applications limiting its integration in some universities and research centers because of lack of budget. The low-cost SCADA system development and integration methodology are an effort to solve the poor cost-effectiveness and low repeatability associated to deploy SCADA systems for microgrid physical testbeds.

As a microgrid controller should be aware of the status of the system, sensing, data collecting, and communications are essential for a microgrid management system. Common parameters to be measured in microgrids are environmental variables such as solar irradiance, temperature, and wind speed. Also, electrical parameters such as frequency, apparent, active and reactive power should be collected into some SCADA systems that are specialized in this type of monitoring sector [33], [34], measuring such electrical parameters allows not only to make forecast for microgrid operation but also to make a microgrid devices health and ageing assessment as presented in [35], [36]. Low-cost monitoring systems are relevant topics, especially for Academic and Research applications where financial budgets are often limited, so efforts have been made for a cheaper solution to collect and display data sensed by energy, gas or environmental sensors for experimental microgrids [37]–[40], as industrial solutions are often expensive and not suitable for small scale applications.

Although monitoring systems are valuable tools for collecting information, an important issue is to have access and consult the data in every part of the world. Every device should be connected to the Internet into what is known as “the Cloud”. To do so, an electronic device must send data over the Internet by means of a communication protocol to keep them stored on a Web database and displaying them on a Web page [41], [42], allowing microgrid interoperability [43]. Related papers mentioned the integration of the Raspberry Pi with Arduino [44], [45]. The development of a low-cost SCADA system for a stand-alone photovoltaic System is presented in [46], the authors measured environmental variables and power generation from the photovoltaic system using an Arduino UNO development board. The cost of development reported is as low as $ 62, however, the SCADA system presented by the authors was limited only to monitoring a single renewable energy source and to wired communication. In [47] it is presented a development of a low-cost SCADA system for remote wireless control and monitoring for a single power inverter. The hardware used by the authors includes an Arduino development board, a Raspberry development board, an ESP12E wireless transceiver and a Wi-Fi shield for Arduino; the implementation cost reported was $ 276, an important cost reduction compared to the estimated $ 750 only for the software in that specific application.

This paper presents the design and implementation of a low-cost SCADA system applied to an experimental microgrid, a much more complex system than the considered one by [46] and [47], as it integrates wireless control and monitoring for several renewable energy sources and storage energy systems for a Renewable Energy Laboratory. The proposed system is an alternative for commercial SCADA and a solution for modular affordable monitoring and control systems for small to medium scale applications.

2.1.3 Proposed system architecture

The HRES for the microgrid at the LabDER-UPV where the low-cost Web-based SCADA system was implemented is composed by a photovoltaic (PV) array, a small-power wind turbine, a biomass gasification plant, a battery-based energy storage system and a fuel backup generator. All the energy sources are connected to a hybrid inverter, which allows the microgrid to operate in both ways: standalone or grid-tied to feed the load as shown in Figure 2. Table 3 shows the main features of the microgrid.

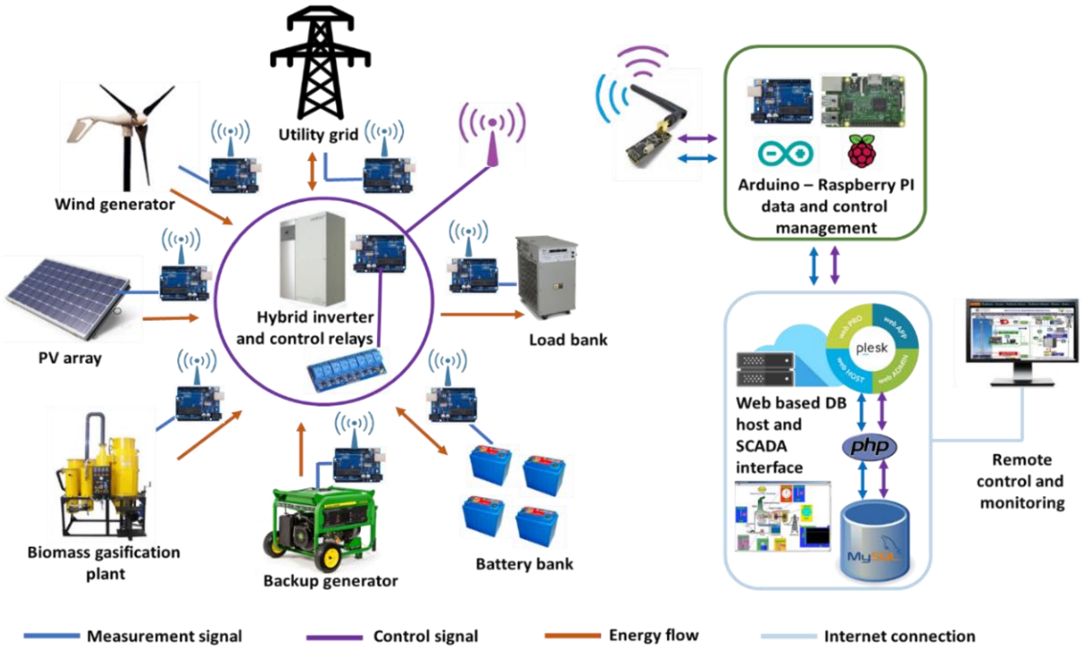


Figure 2 Overall system architecture. Taken from [134].

Table 3 LabDER-UPV microgrid main features.

Description	Main features
Photovoltaic array	2.1 kW, 12 solar panels. Connected to a Xantrex GT solar inverter.
Wind power system	3.5 kW @ 12 m/s wind speed. Installed on a 24-meter tower from ground level.
Biomass power plant	10 kWe @ 30 Nm3/h from syngas. 13 kg/h biomass consumption from wood chips and pellets.
Battery bank	12 kWh power capacity, 4 batteries from 12 V @ 250 Ah.
Fuel backup generator	Petrol 9 kW, 230 VAC @ 50 Hz PRAMAC S12000.
Test-load bank	10 kW, 240 VAC @ 50 Hz resistive load bank

* Taken from [10].

Figure 3 shows a general electrical connection overview between the different energy sources and the loads in the microgrid. All the sources were connected through power converters and inverters to a 230 VAC at 50 Hz bus.

The wind power generation system and the photovoltaic array work in parallel. However, the syngas power generator fed by the gasification plant and the fuel backup generator cannot work at the same time since the central inverter has only one input for AC generators and none of the generators has a synchronization system.

The microgrid can operate in two different configurations; stand-alone mode and grid-tied mode (tied to the utility grid over a Xantrex XW hybrid central inverter). Both modes of operation are available on the designed SCADA Web system.

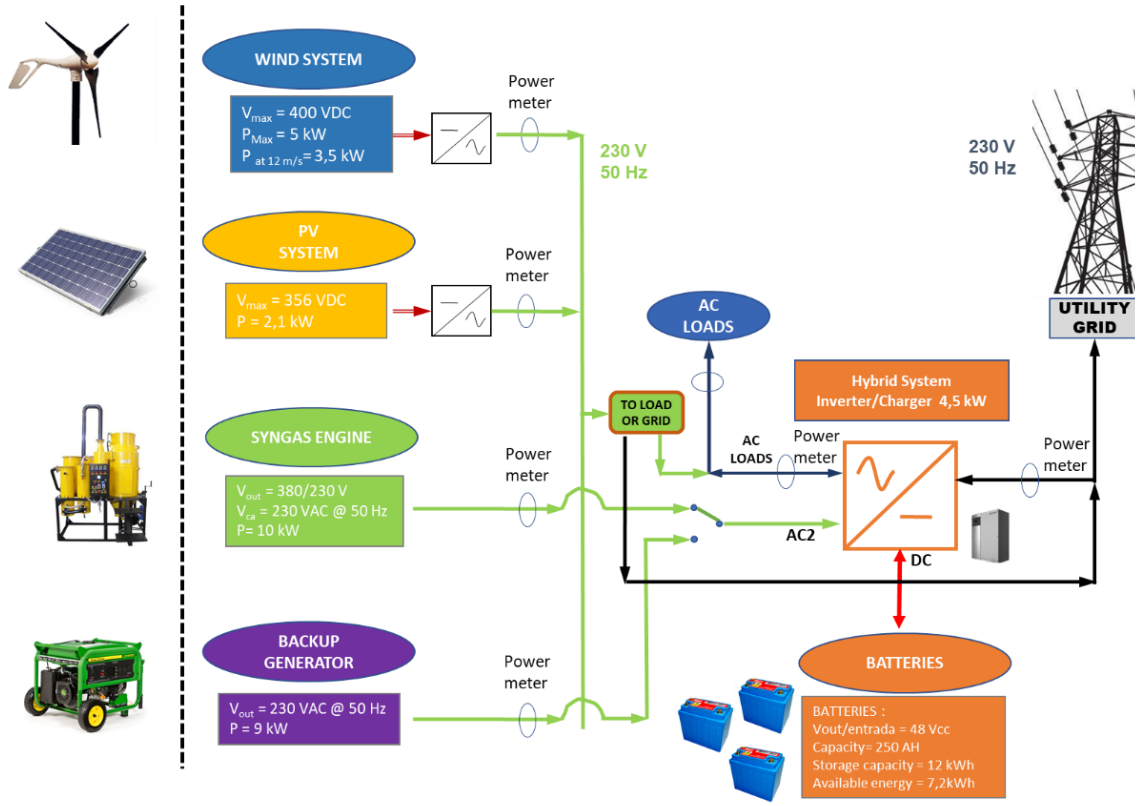


Figure 3 Microgrid electrical connection overview.

Building a low-cost SCADA system for microgrid applications requires the development and integration of several hardware and software implementations. Figure 4 shows the 230 V AC microgrid that has been setup in LabDER-UPV, indicating system data and energy flows. Optionally, if it is required, the microgrid can be connected to the utility grid. The renewable and backup energy sources are connected to a common AC bus managed by a Xantrex XW hybrid inverter, which communicates wirelessly to an Arduino-Raspberry PI base station for data, and control signal management. Remote control and monitoring the microgrid is available through a Web host with a MySQL database.

The Web hosting platform used is PLESK which allows users to setup Websites and configure a Web server through a control panel with a simple, intuitive, and easy-to-use interface. PLESK bases its programming language in PHP and MySQL, the used versions of each were 7.1 and 5.5 respectively.

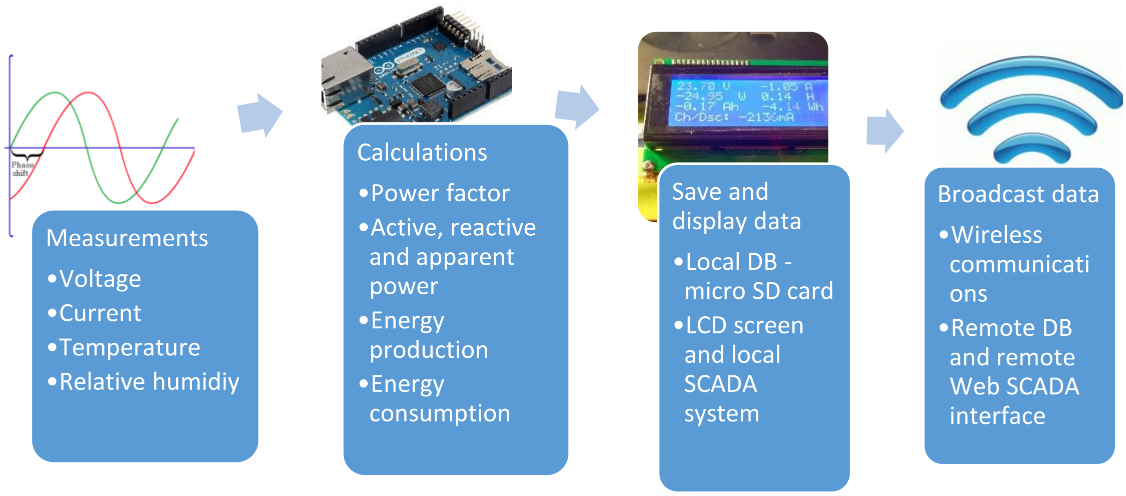


Figure 4 Arduino wireless power meter (AWPM) main tasks.

2.1.4 Methodology and case study

The implemented low-cost experimental microgrid platform has a functional cloud-based own-developed SCADA system, as previously shown in Figure 2. Table 4 and Table 5 shows the environmental and electrical parameters measured, respectively, as well as the measurement device and Arduino program libraries used. The libraries used for the Arduino code have been recommended by the device manufacturer, and as explained later, some libraries have been modified to obtain more information from the measuring device. At the end, the main contribution of this work is to create a proceeding to integrate all the measurement devices required in an entire system to obtain a low-cost measure arrangement.

2.1.4.1 Design of measurements and control devices

Table 4 shows the parameters which must be measured in the microgrid. It is a requirement to have special hardware and software to perform the measurements. For the electrical variables, was designed and set up an Arduino wireless power meter (AWPM). Its main tasks are shown in Figure 4. Inside the AWPM, an electric measures voltage and current, the Arduino carries out calculations using the energy monitoring library presented in Table 5. An integrated Arduino-based base station broadcasted the data via wireless using the radio frequency transceiver module NRF24L01 by means of the SPI (Serial Peripheral Interface) synchronous protocol, which allows the AWPM to send all the electrical parameters gathered.

Table 4 Environmental parameters measured in the microgrid under study.

Environmental measurements	Units	Sensor	Measuring range	Measurement device
Solar irradiance	W/m^2	CEBEK C0121 Solar cell	0 – 1100 W/m^2 +-40W/m^2	Own developed Arduino based data logger: Multiple sensors readings, data recordings, and wireless communication enabled. EmonLib.h and LiquidCrystal.h libraries were used for measuring and displaying energy parameters, respectively.
Environmental temperature	°C	DHT22	-40 - 80°C +-0.5 °C	
Wind speed	m/s	FGHGF Anemometer 0-5V	0 – 32,4 m/s +- 1 m/s	
Relative environmental humidity	%	DHT22	0 - 100% +- 5%	

* Taken from [10].

Figure 5 shows the Arduino code developed for the AWPM, libraries, and variables measured and calculated are also shown. Calibration of the current and voltage measurements is an important issue for the AWPM implementation, this task is carried out by adjusting the calibration coefficients shown in the code, line 6 and 7. Coefficients are selected by means of value measurement comparison of the AWPM with a commercial Sentron PAC3200 Power Meter for well-known AC and DC loads, so the mean difference between the AWPM and the Sentron PAC 3200 measurements is less than +-5% on average

Table 5 Electrical parameters measured in the microgrid under study.

Electrical measurements	Units	Sensor	Measuring range	Measurement device
Current	A	YHDC SCT-013-030	0-100 A +-3%	Own developed Arduino based single phase power meter:
Voltage	V	PCB Mount Transformer VB 2.3/2/12	200 – 260 V +-1V	Arduino based power meters were located along the microgrid and developed using voltage and current sensors. EmonLib.h and EmonCalc.h (libraries provided by openenergymonitor.org) perform the power and energy calculations. [48] Radiofrequency wireless communications libraries were provided by arduinolibraries.info/libraries/rf24.
True Power	W	Calculated		
Reactive Power	VAR			
Apparent Power	VA			
Power factor	-			
Frequency	Hz			
Energy consumption	kWh			
Energy generation	kWh			

* Taken from [10].

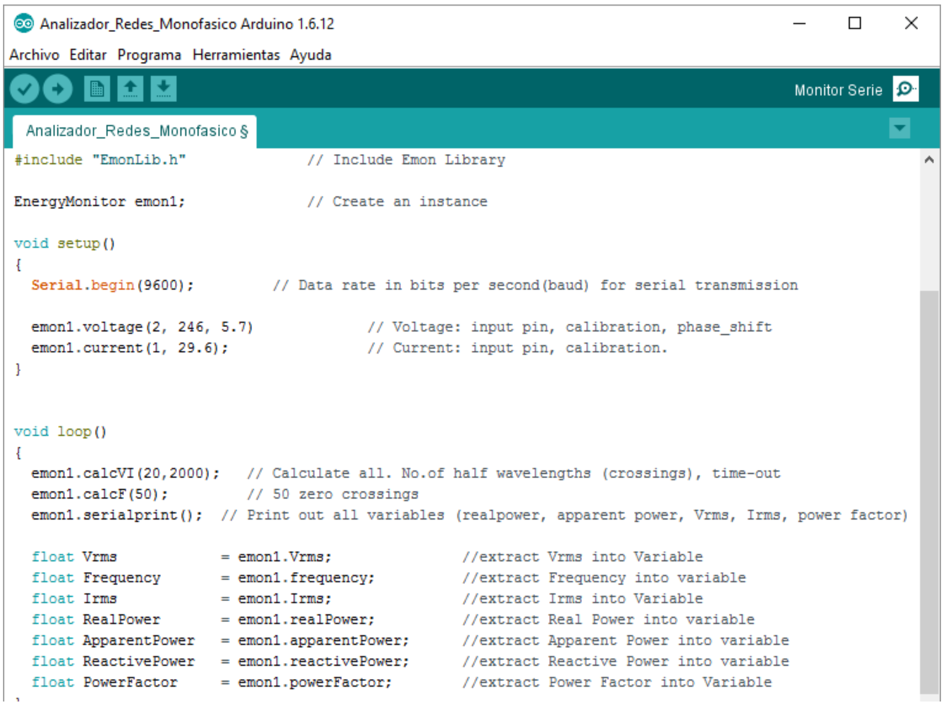


Figure 5 Arduino code for the Wireless Power Meter with variables and libraries used.

The AWPM designed operates with a voltage transformer and an SCT-013 non-intrusive current transformer sensor. The transformer turns ratio is 12:1, reducing de grid voltage to a safety level that can be adjusted by a voltage divider, reduced to the Arduino analog input voltage level (0-5 VDC). To measure the voltage, it is used the analog input A2. The current transformer SCT-013 measures the instantaneous current and the Arduino reads the value by means of the analog input A1. Figure 6 shows the connection of the main components for the AWPM.

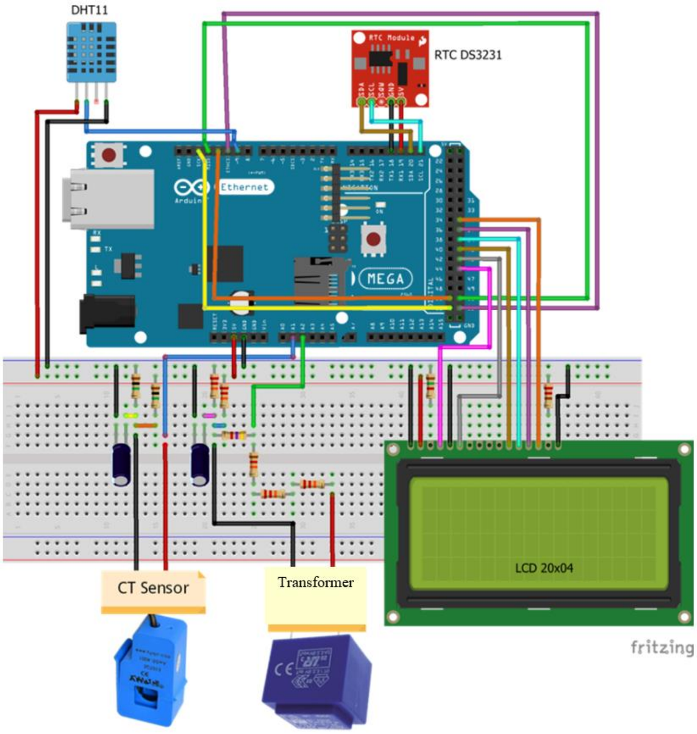


Figure 6 AWPM main components connection diagram.

Power factor measures the phase displacement between voltage and current by means of zero-crossing detection algorithm programmed in the power calculations library used for the AWPM. A threshold system equation for the zero-crossing detection algorithm can be proposed for the current and voltage measurements based in the work of [49], [50], and [51] were it is possible to model the interaction between continuous time functions and discrete event models. A continuous function behaviour [52] can be modelled by a differential equation in the form of $\dot{x} = f_x(x, u, t)$ and an indicator discrete-event function with the form of $g_x(x, u, t)$, argument of this both equations are the subset of state, input and independent variables such as time. When indicator discrete-event function changes of sign from positive to negative or vice versa, a discrete event denoted by ∂ occurs, this is referred to be a zero-crossing detection. Equation 1 shows the relation between the continuous and discrete event functions referred to their sign changes.

$$\dot{x} = \begin{cases} f_1(x), & g(x,t,u) \geq 0 \\ f_2(x), & g(x,t,u) < 0 \end{cases}$$ Eq. (1)

Where $g(x, t, u)$ is the zero-crossing detection function. Active power, apparent power, reactive power and, power factor are calculated by means of Eq. (4), (5), (6) and (7) respectively, taken from [53] for AC circuits analysis.

$$V_{RMS} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} V^2(n)}$$ Eq. (2)

$$I_{RMS} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} I^2(n)}$$ Eq. (3)

$$P = \frac{1}{N}\sum_{n=0}^{N-1} V(n) \cdot I(n)$$ Eq. (4)

$$S = V_{RMS} \cdot I_{RMS}$$ Eq. (5)

$$Q = \sqrt[2]{\|S^2 - P^2\|}$$ Eq. (6)

$$\cos\varphi = \frac{P}{S}$$ Eq. (7)

V_{RMS} is the voltage root mean square value, in Eq. (2); I_{RMS} is the current intensity root mean square value, in Eq. (3); P is the active power, in Eq. (4); S is apparent power, in Eq. (5); Q is reactive power, in Eq. (6) and $\cos\varphi$ is the power factor, in Eq. (7). To perform the calculations of each power type it is important to consider discrete root mean square values for voltage and current measurements. Figure 7 shows the flowchart of calculations based on Equations 4, 5, 6 and 7 to calculate the active, reactive, and apparent power in addition to the power factor.

```
//Cálculos para los valores de potencia
realPower = V_RATIO * I_RATIO * sumP / numberOfSamples; // Potencia activa
apparentPower = Vrms * Irms;    // Potencia aparente
reactivePower = sqrt(abs((apparentPower*apparentPower)-(realPower*realPower))); // Potencia reactiva
powerFactor=realPower / apparentPower;  // Factor de potencia
```

Figure 7 Flowchart of electrical calculations to obtain power factor, active, apparent and reactive power.

The Emonlib.h library for Arduino performs the rest of the calculations. This library has been modified to additionally measure frequency. Figure 8 shows the code to calculate the grid frequency.

The segment parts of the algorithm programming on the Arduino software following the zero-crossing method to do the calculation seen previously in Equation is presented. This algorithm detects every time an AC signal crosses zero after reading the analog pin reference by the voltage transformer connected to the Arduino board, within the 10-bit resolution range of the analog to digital converter (ADC). When a value is between 512 and 520 (intermediate range of $2^{10} = 1024$ possible values) means that the signal has crossed the zero reference of the AC voltage.

Another Arduino board collects all the meteorological data via wireless. Figure 9b shows its overall design. The Arduino wireless meteorological data collector (AWMDC) measures wind speed, solar radiation, environmental temperature, and humidity with a DHT22 sensor. Again, a base station receives the data and broadcasts them via wireless communication using the NRF24L01 Radiofrequency transceiver module.

The control of the microgrid requires connecting and disconnecting the energy sources to feed the loads or to carry out the desired test. The Arduino wireless switch controller (AWSC) accomplishes this task. Figure 9c shows its overall structure. The AWSC consists of an Arduino Mega board, a radiofrequency transceiver module NRF24L01, and a Relay module. Its operation depends on commands sent by the Arduino-Raspberry Pi 3 wireless base station (ARWBS), shown in Figure 9d.

```
// FREQUENCY
//-----------------------------------------------------------------------------------
void EnergyMonitor::calcF(int crossings) {
boolean stf = false;
unsigned long first, second;
unsigned long delta = 0;

while(stf == false) {                                    //wait for first crossing
  startF = analogRead(inPinV);                          //using the voltage waveform
  if ((startF > 512) && (startF < 520)) {
   stf = true;  //check its within range
   first = millis();
   delay(4); } //Make sure no second read is in this range
}
stf = false;
for(int i = 0 ; i < crossings ; i++) {
  while(stf == false) {                                   //wait for next crossing
   startF = analogRead(inPinV);                          //using the voltage waveform
   if ((startF > 512) && (startF < 528)) {
    stf = true;
    second = millis();
    delta += (second - first); //Add time between crossings
    first = second;
    delay(4); } //Make sure no second read is in this range
  }
  stf = false; }
frequency = (crossings / 2) / ((double)delta / 1000); }
```

Figure 8 AWPM frequency calculation code.

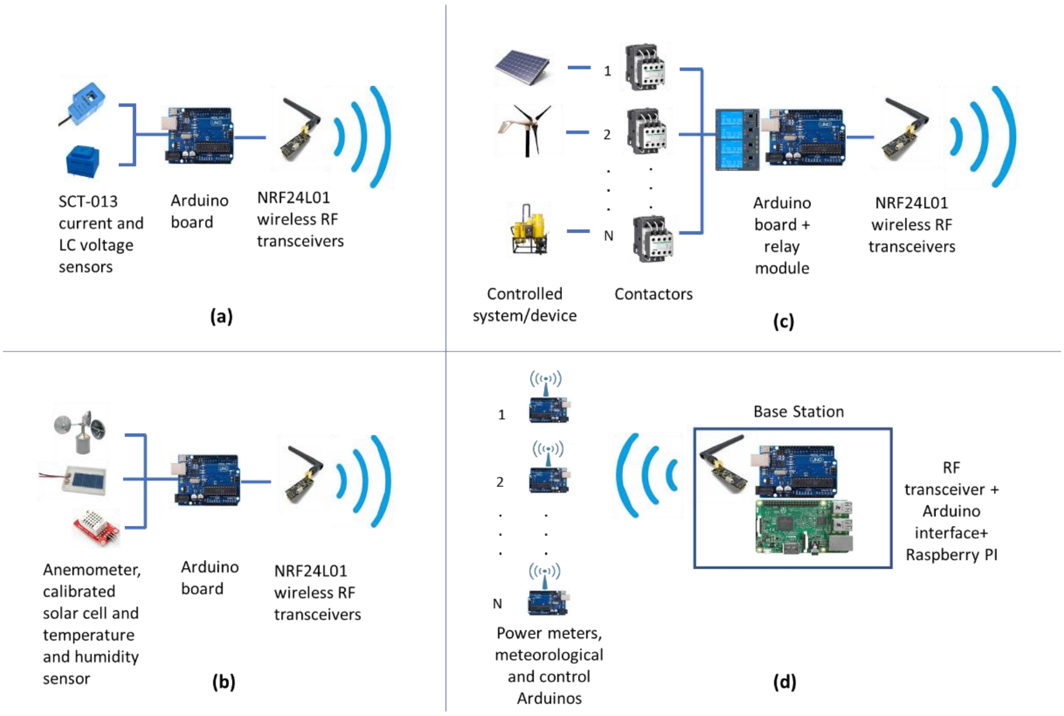


Figure 9 (a) Arduino wireless power meter; (b) Arduino wireless meteorological data collector; (c) Arduino wireless switch controller; (d) Arduino-Raspberry PI 3 wireless base station.

The ARWBS manages information and operation rules within the microgrid, this device consists of the integration of an Arduino board and a Raspberry Pi, allowing the system to log data and store it into a local DB, as well as in a cloud DB.

The communications of the Arduino and Raspberry Pi 3 bases on the I2C serial protocol, with this, the Arduino operated as an interface between the Raspberry Pi and all the other Arduino-based data collectors. A SCADA system Website user interface has been developed to control and monitor the entire microgrid, this interface is linked to the ARWBS by TCP/IP communications and hosted in PLESK Web using a MySQL DB.

2.1.4.2 Communications and data logging

An NRF24L01 Radiofrequency transceiver carries out the wireless communications, operating at 2.4 GHz using an SPI protocol to manage the communication with an Arduino board. All the AWPMs, AWMDC, and AWSC are wirelessly linked into the ARWBS using radiofrequency as shown in Figure 10. The user interacts with the microgrid over the own-developed Web SCADA interface using HTML5, JavaScript and PHP programming languages, hosted on the PLESK Web server. Cloud DB reads and writes data that are constantly updated, at preset time intervals for each variable, as data refresh and/or operation commands sent by the ARWBS to each microgrid device. Also, a local DB records the information as a backup for preventing data losses due to wireless communication or internet connection failures.

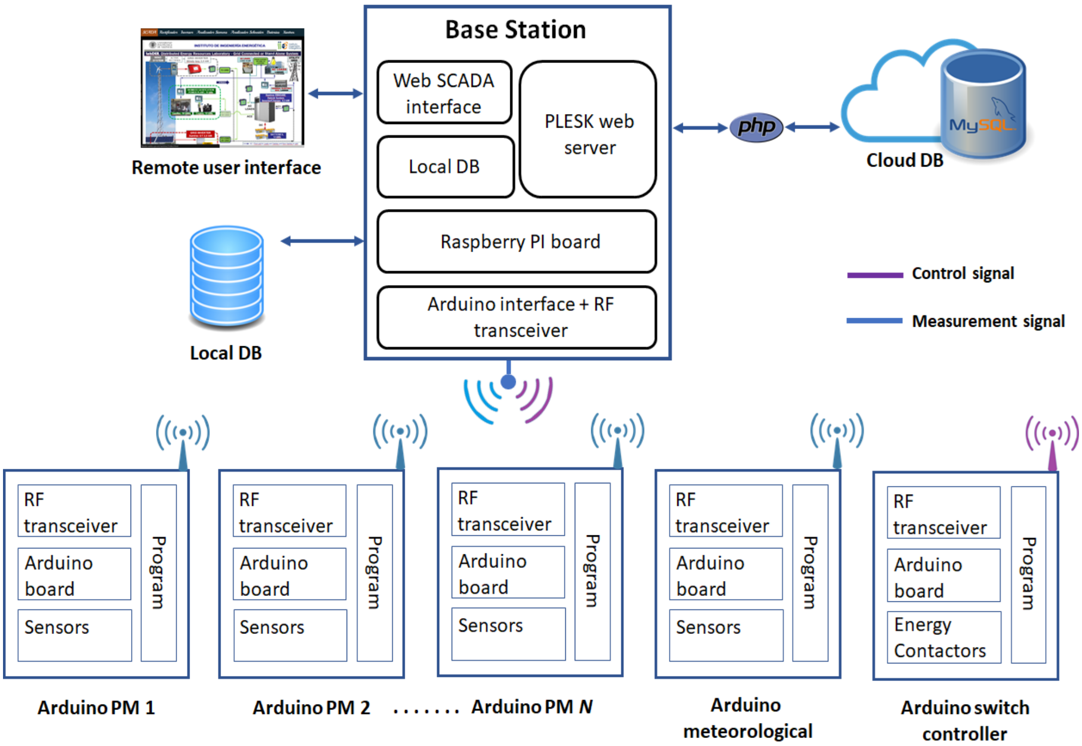


Figure 10 Communications structure.

2.1.4.3 Cloud DB and Web SCADA

The user interacts with the microgrid using a Web SCADA interface that operates over a MySQL cloud DB, writing and consulting data from it on an own-developed Graphical User Interface (GUI). PHP makes queries from Web SCADA GUI through the PLESK platform and, subsequently, modifies the MySQL cloud DB, updating its data, according to user commands or automated data refresh from the measurement devices. Figure 11 shows the general data transmission process from each microgrid device into the MySQL cloud DB all over the ARWBS along with the communications ports.

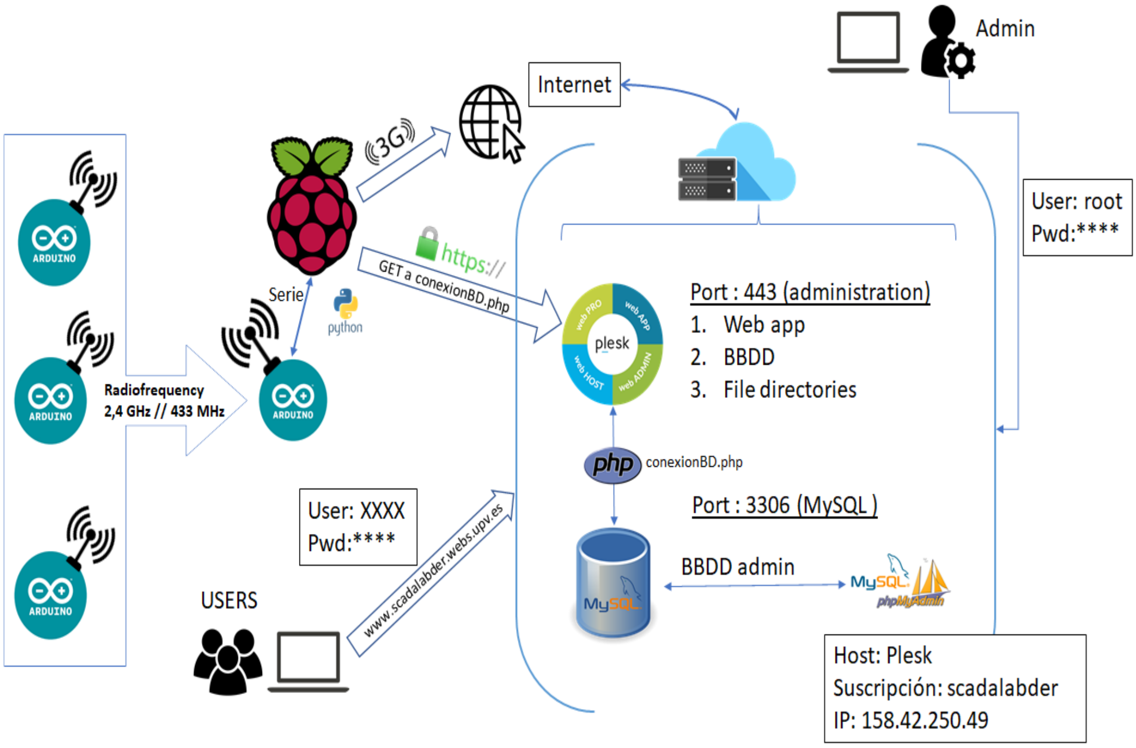
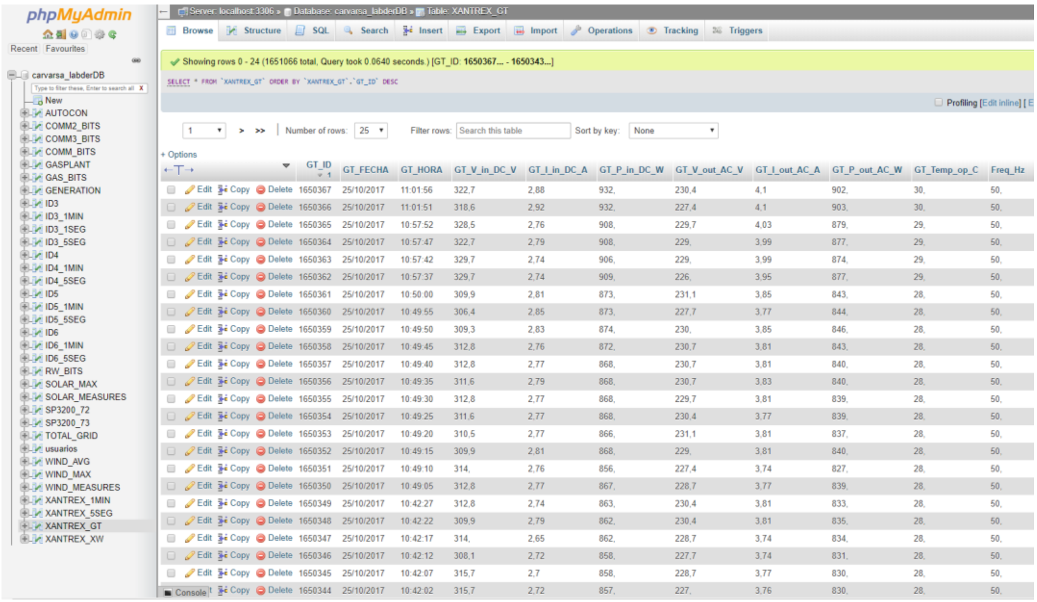


Figure 11 Connection with MySQL DB.

After communication is established between Plesk web server and MySQL DB, the next step is to locate every table created in the database and write new information from AWPM in a real-time monitoring data set. As there are many devices connected and sending information to the Remote MySQL DB, the Web SCADA needs to fetch data of all tables created for the power meters, the meteorological measurements, and the status of the contactor. The communication between the DB and the raspberry pi is carried out by means of 3G modem, using a SIM card, but it is possible to use a Wi-Fi network obtaining the same results. Every data from the sensors is stored in real time in the database.

Over time, more data will be recorded increasing the size of the table and therefore, the space memory will reach the limit storage permitted by a Plesk regular account (6 GB). Moreover, it will require more data if the storing rate is every second for all variables. To overcome this, a maintenance schedule is programmed every year, giving time to back up the saved data and erasing the older information. Figure 12 represents the information obtained from a grid-tied PV inverter. Such data is stored in the MySQL DB.



GT_ID	GT_FECHA	GT_HORA	GT_V_in_DC_V	GT_I_in_DC_A	GT_P_in_DC_W	GT_V_out_AC_V	GT_I_out_AC_A	GT_P_out_AC_W	GT_Temp_op_C	Freq_Hz
1650367	25/10/2017	11:01:56	322,7	2,88	932,	230,4	4,1	902,	30,	50,
1650366	25/10/2017	11:01:51	318,6	2,92	932,	227,4	4,1	903,	30,	50,
1650365	25/10/2017	10:57:52	328,5	2,76	908,	229,7	4,03	879,	29,	50,
1650364	25/10/2017	10:57:47	322,7	2,79	908,	229,	3,99	877,	29,	50,
1650363	25/10/2017	10:57:42	329,7	2,74	906,	229,	3,99	874,	29,	50,
1650362	25/10/2017	10:57:37	329,7	2,74	909,	226,	3,95	877,	29,	50,
1650361	25/10/2017	10:50:00	309,9	2,81	873,	231,1	3,85	843,	28,	50,
1650360	25/10/2017	10:49:55	306,4	2,85	873,	227,7	3,77	844,	28,	50,
1650359	25/10/2017	10:49:50	309,3	2,83	874,	230,	3,85	846,	28,	50,
1650358	25/10/2017	10:49:45	312,8	2,76	872,	230,7	3,81	843,	28,	50,
1650357	25/10/2017	10:49:40	312,8	2,77	868,	230,7	3,81	840,	28,	50,
1650356	25/10/2017	10:49:35	311,6	2,79	868,	230,7	3,83	840,	28,	50,
1650355	25/10/2017	10:49:30	312,8	2,77	868,	229,7	3,81	839,	28,	50,
1650354	25/10/2017	10:49:25	311,6	2,77	868,	230,4	3,77	839,	28,	50,
1650353	25/10/2017	10:49:20	310,5	2,77	866,	231,1	3,81	837,	28,	50,
1650352	25/10/2017	10:49:15	309,9	2,81	868,	229,	3,81	840,	28,	50,
1650351	25/10/2017	10:49:10	314,	2,76	856,	227,4	3,74	827,	28,	50,
1650350	25/10/2017	10:49:05	312,8	2,77	867,	228,7	3,77	839,	28,	50,
1650349	25/10/2017	10:42:27	312,8	2,74	863,	230,4	3,81	833,	28,	50,
1650348	25/10/2017	10:42:22	309,9	2,79	862,	230,4	3,81	835,	28,	50,
1650347	25/10/2017	10:42:17	314,	2,65	862,	228,7	3,74	834,	28,	50,
1650346	25/10/2017	10:42:12	308,1	2,72	858,	227,7	3,74	831,	28,	50,
1650345	25/10/2017	10:42:07	315,7	2,7	858,	228,7	3,77	830,	28,	50,
1650344	25/10/2017	10:42:02	315,7	2,72	857,	227,	3,76	830,	28,	50,

Figure 12 Information obtained from the sensors and stored in the cloud DB.

The data is collected every second and the Web SCADA fetch data from MySQL DB, written in SQL queries with PHP acting as a link of the remote web interface and DB server. The PHP query sentences aim to access the voltage, current, power, and energy data located in their respective column of the table.

Figure 13 shows the fetching code to read and update data register from the DB. To do so, it requires specifying the exact name as it is stored in the database. In order to display the information correctly, it must be converted from a string format into a numerical value. Then, the units of each parameter are added.

scada.php

```php
<?php
$PM1 = $conn->query("SELECT ARD_REAL_POW, ARD_NOM_VOLT, ARD_NOM_CURR, ARD_I_A_E FROM ARDUINO_PM ORDER BY ARD_ID DESC LIMIT 1");
if ($PM1->num_rows > 0) {
    while ($rowARD = $PM1->fetch_assoc()) {
        $ARD_Power = str_replace(',','.',$rowARD['ARD_REAL_POW']);
        $ARD_Power = (float)$ARD_Power/1000;
        $ARD_Voltage = str_replace(',','.',$rowARD['ARD_NOM_VOLT']);
        $ARD_Voltage = (float)$ARD_Voltage;
        $ARD_Current = str_replace(',','.',$rowARD['ARD_NOM_CURR']);
        $ARD_Current = (float)$ARD_Current;
        $ARD_ImAcEn = str_replace(',','.',$rowARD['ARD_I_A_E']);
        $ARD_ImAcEn = (float)$ARD_ImAcEn;
        echo 'ARDUINO PM'.'<br>'.number_format($ARD_Power,2).' kW'.'<br>'.number_format($ARD_Voltage,2).' V'.'<br>'.number_format($ARD_Current,2).' A'.'<br>'.number_format($ARD_ImAcEn,2).'    kWh';
    }
}
?>
```

Figure 13 PHP request to fetch data from the MySQL DB.

As previously mentioned, the user operates the microgrid through an own-developed Web SCADA interface, then the Web interfaces make PHP queries to the PLESK server via port 443 and to the cloud DB using port 3306 through the ARWBS using TCP/IP. There are three types of data register tables within the cloud DB: data storing registers, microgrid operation registers and user credential registers. Information displayed in the Web interface is refreshed by timely queries requests, according to internal adjusts. When it is required to activate/deactivate a load or an energy source, the user (or according to the preset programming) sends a request to cloud DB by means of Web SCADA, such request is read by the ARWBS and then it sends another request to the AWSC which finally close or open the physical switches or relays. Figure 15 shows the own-developed Web SCADA interface main menu.

As all devices connect to the remote PLESK server, over the ARWBS, which hosts the Web SCADA interface developed user, interacts with the system by means of an HTML5 graphical user interface, allowing the user to set up operation parameters for the microgrid as well as the complete system monitoring and supervising. It is possible also to save and export data from the Plesk server to another format as is shown in figure 14.

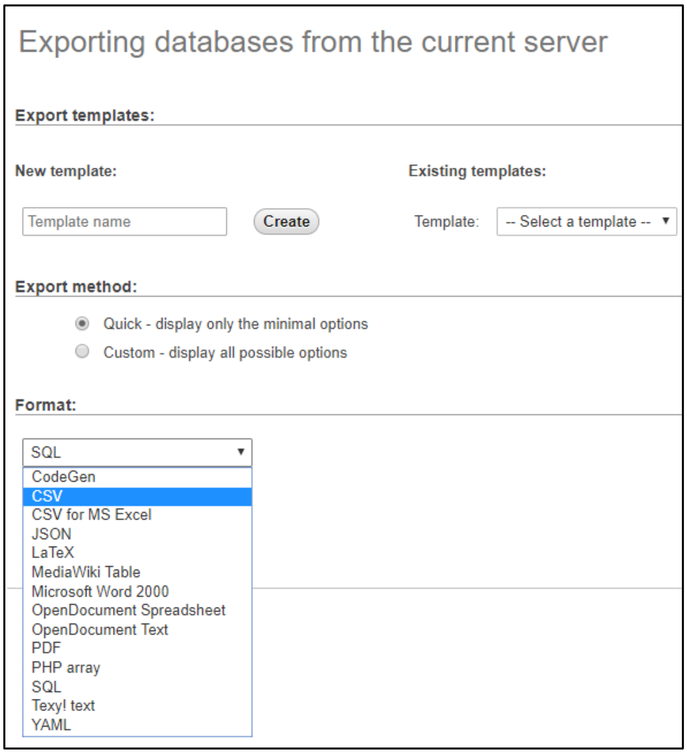


Figure 14 Formats available in Plesk to export data from the MySQL DB.

2.1.5 Results and discussion

To test the low-cost SCADA system functionality and its performance several experiments were carried out in the Laboratory of Renewable Energies at Universitat Politècnica de València using the microgrid previously presented in Figure 3. The energy flow to and from the microgrid is also appreciated in Figure 2, as well as the flow of data and control signals, together with the storage of information in a remote database and the access to a remote monitoring and control graphical interface developed in HTML5 and JavaScript over an internet connection. As a result of the monitoring Arduino-based devices implementation, the software and the database development, a system topology, was obtained a SCADA system, as shown in Figure 15. Figure 16 shows the curves obtained from a short-term experimental functionality test for power data collecting.

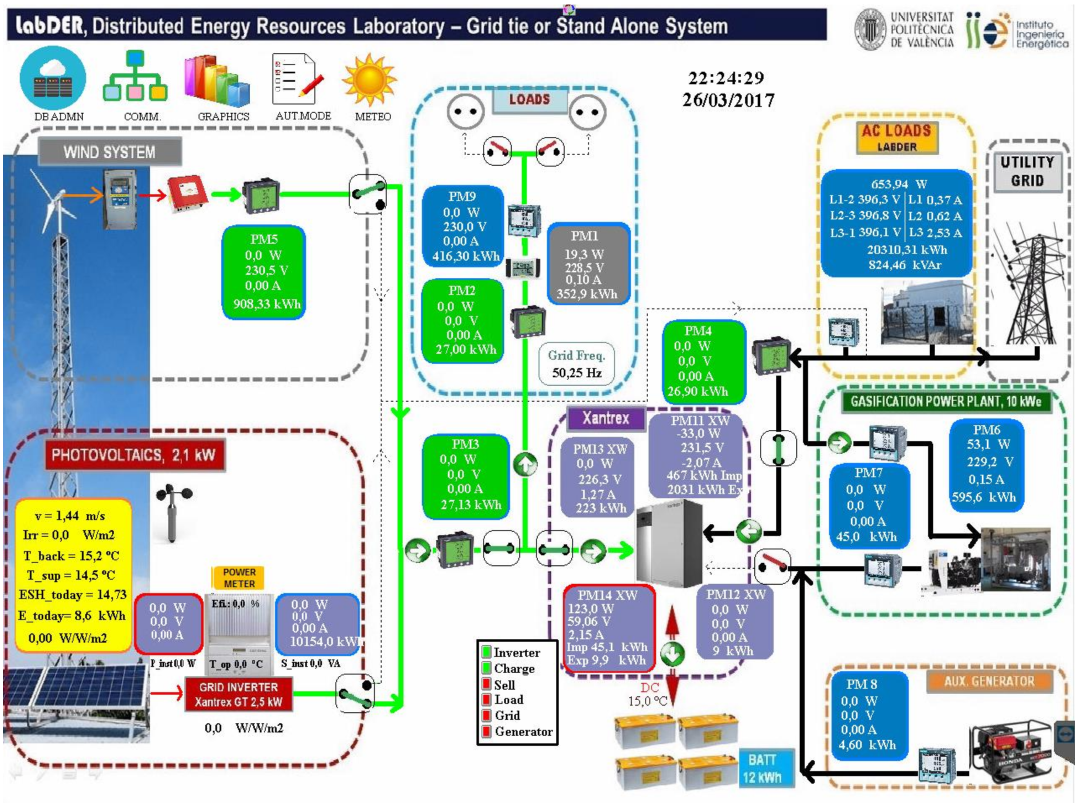


Figure 15 HTML5 Web SCADA interface main menu.

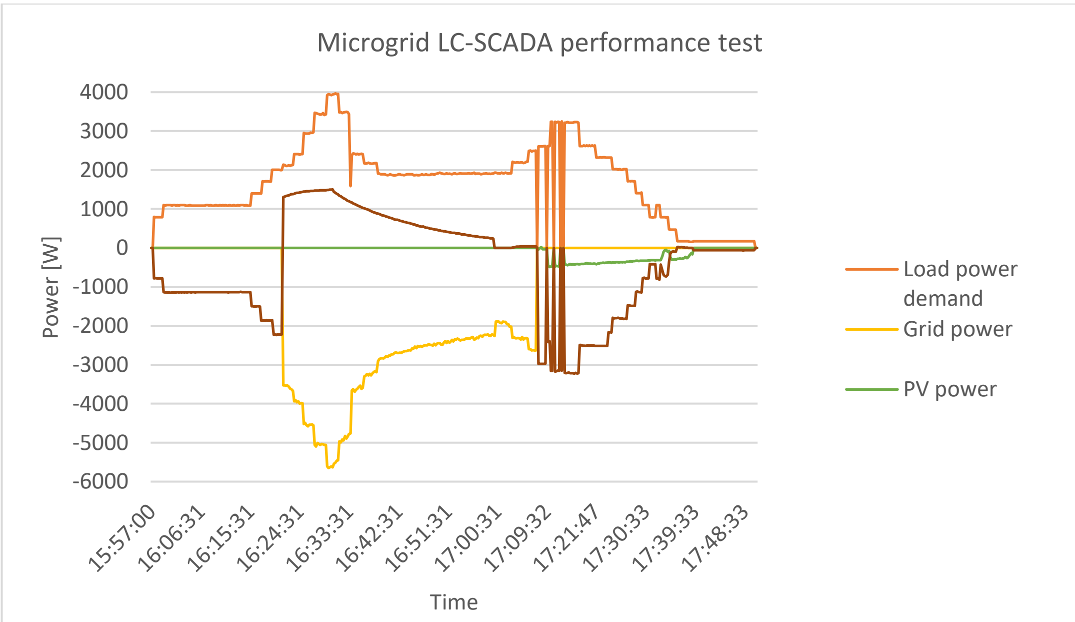
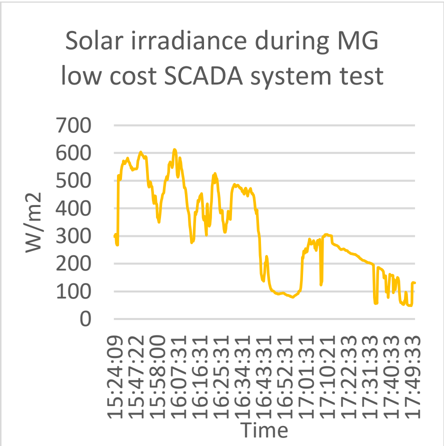


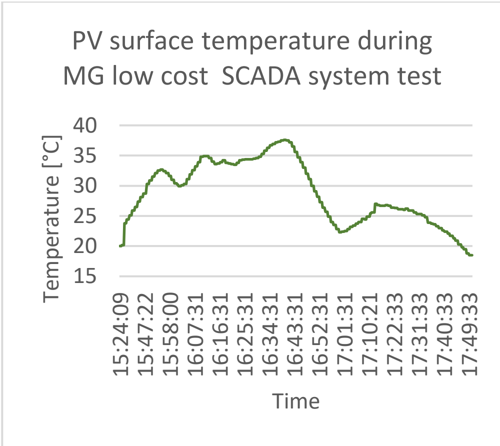
Figure 16 LC-SCADA system data acquisition test over the microgrid.

For the tests was necessary to deploy and establish communication between the AWPMs, the AWMDC, the AWSC, and the ARWBS as well as the Web server. In the experiment, a load demands energy from the microgrid, starting from 800 W to a maximum of 3.97 kW, alternating between power supply from the PV array, the utility grid, and the battery bank. Positive values represent the energy demanded by the system and negative values correspond to supplied by the energy sources. It can be noticed that the battery bank sometimes works as a load and sometimes works as a source, as usual in this kind of storage systems.

On the other hand, PV power was affected by cloudy skies, meteorological data was gathered by the AWMDC. The maximum solar irradiance during this short test was 600 W/m^2 at 35 °C on the surface of solar panels as shown in Figure 17.



(a)



(b)

Figure 17 (a) Solar irradiance and (b) PV surface temperature data collecting test for a short-term functionality test of LC-SCADA system.

Also, are shown two long-term data collecting tests results using the low-cost SCADA system, one of a one-day duration and another of a one-week duration. Figure 18 shows the one-day test. In this figure, it is possible to appreciate the power generated by the wind turbine and the PV array accordingly to the current meteorological conditions present during the day, as well as the power load demand derivate from the daily activity inside the Laboratory of Renewable Energies. These activities include the use of lights, personal computers from researchers etc. as well as the low-cost SCADA system related devices. Load power demand ranges on average from 0.3 to 3.3 kW.

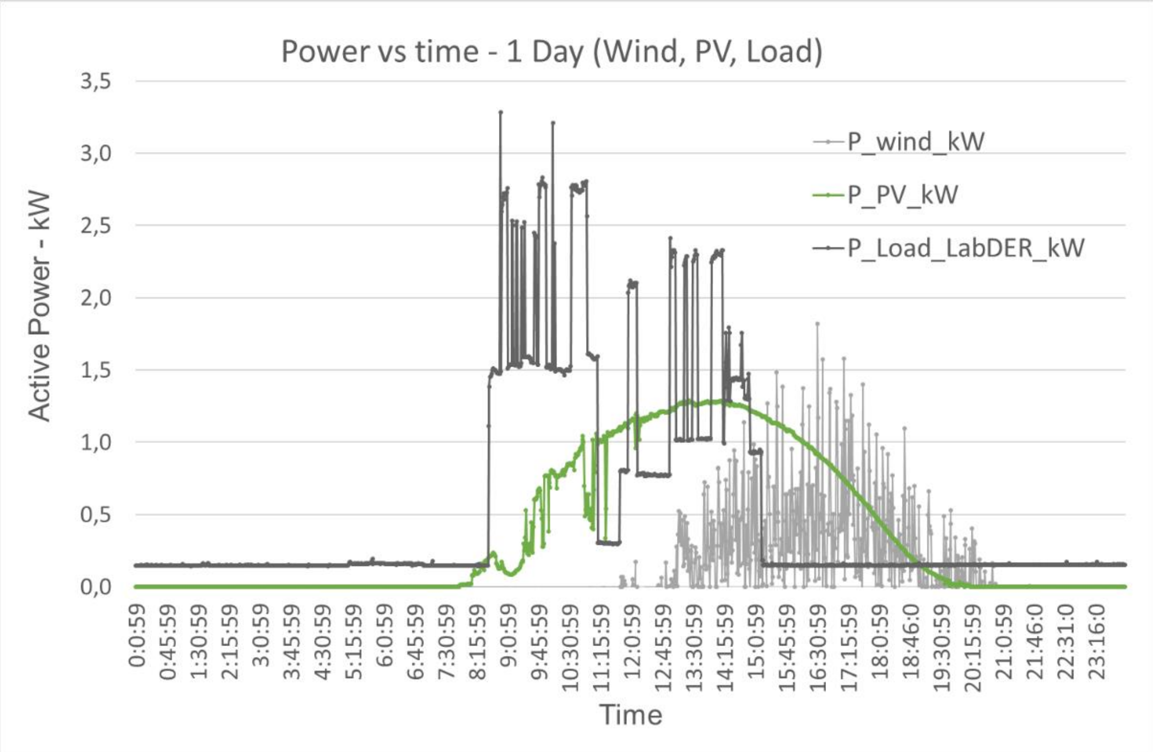


Figure 18 One-day long functionality LC-SCADA system test under nominal load demand.

The third test presents a one-week duration of the experiment. Figure 19 shows the obtained plot for wind power, solar power, and users power demand. As can be appreciated in Figure 18, there was an important wind power generation from Monday to Thursday and on Sunday, while Friday and Saturday there were not windy days; meanwhile, solar PV power generation was almost constant except for Sunday, when the sky was cloudy.

This one-week test shows that it is possible to obtain data in a continuous way. The reliability of the system is enough for obtaining the data required for analysing the system.

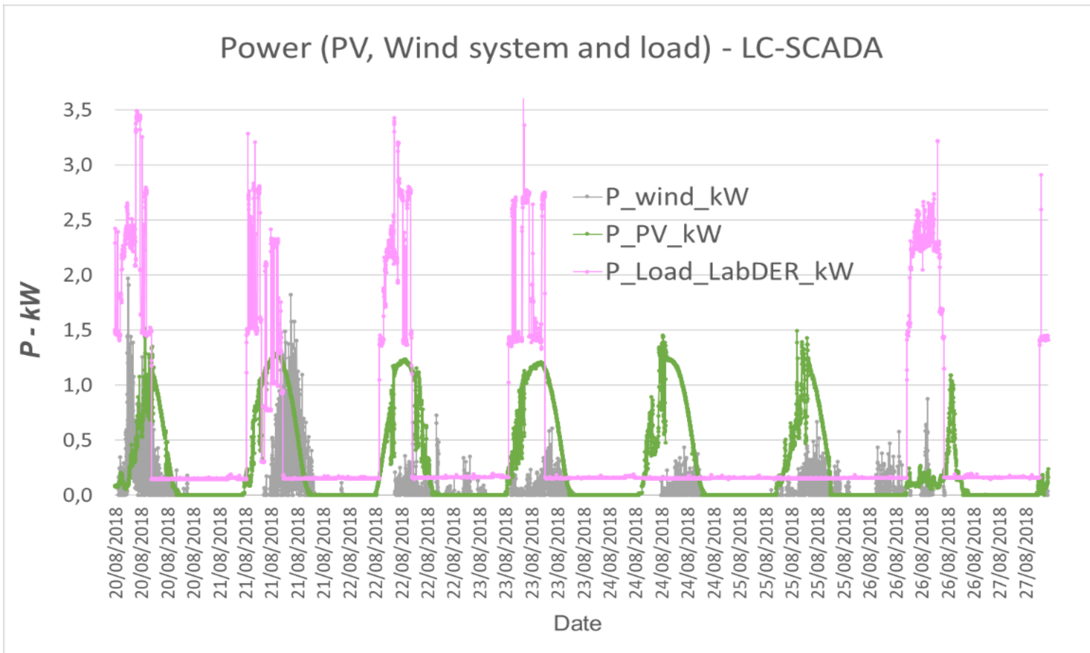


Figure 19 One-week duration LC-SACADA test, from Monday to Sunday.

Table 6 shows the average standard deviation from the difference between values obtained comparing the AWPM and a SIEMENS Sentron PAC3200. For a set of 6,506 measurements the AWPM measurement performance test was carried for two cases: grid-tied mode and stand-alone mode operation of the microgrid.

Table 6 The average standard deviation between AWPM and Sentron PAC3200 power meter measurements

Variable	Average standard deviation for grid-tied experiment	Average standard deviation for stand-alone experiment
Active power	2.720	2.268
AC bus Voltage	1.734	1.121
AC bus Intensity	0.068	0.107
AC bus Frequency	0.058	0.079

As shown in Table 6, the highest average deviation occurs in the voltage measurement for both cases, this causes the high average deviation value for the active power measurement. Values presented are the standard deviation from a set of a total of 6,506 measurements for each variable. It is notable how the microgrid has a better bus frequency performance when it is working in a grid-tied mode with a more accurate measurement comparing the AWPM and the Siemens Sentron PAC 3200. On the other hand, when the microgrid operates in standalone mode it is more complicated to have a stable frequency within it, therefore, exists more average standard deviation discrepancies for the bus frequency measurement. This data analysis between data collected for the own-developed Arduino based power meter and a commercial Sentron PAC 3200 denotes that the AWPM is a reliable solution for low-cost data acquisition systems.

Table 7 shows the price (Euros) for the low-cost SCADA components according to the Amazon.es and Plesk.com Websites. Table 8 shows the price (Euros) of the main components for a standard SCADA system solution using brandmark components. Prices as listed in PCE-instruments.com, Mouser.es, Plesk.com, and Amazon.es Web sites. The total implementation cost for the low-cost SCADA system developed is 1.115 €, meanwhile, a similar solution implemented with brandmark devices costs around 9,360 €. It took six months to develop the low-cost SCADA, while the brandmark system was implemented in about three months plus management and maintenance scheduling of the equipment.

Table 7 LC-SCADA system implementation cost.

Device	Qty	Unit Cost	Import
Arduino based wireless single-phase Power Meter. Contains 1 Arduino UNO, 1 ethernet shield, 1 NRF24L01 transceiver, 1 SCT-013 current transformer, 1 VB 2.3/2/12 voltage isolated transformer, and miscellaneous accessories.	9	100 € [1]	900 €
Arduino - Raspberry PI base station. Contains: 1 Arduino UNO, 1 NRF24L01 transceiver, 1 Raspberry Pi and miscellaneous accessories.	1	80 € [1]	80 €
Arduino based wireless meteorological module. Contains 1 Arduino UNO, 1 NRF24L01 transceiver, 1 DHT temperature and humidity sensor, 1 solar irradiance sensor, 1 anemometer analog input reading.	1	50 € [1]	50 €
Arduino based wireless switching module. 1 Arduino UNO, 1 NRF24L01 transceiver, 1 8-channel relay output relay.	1	25 € [1]	25 €
PLESK Web server annual fee	1	60 € [2]	60 €
Web SCADA system interface	1	Free	Free
Other[1]	1	200 € [1]	200 €
TOTAL			1,315 €

[1]Unitary cost prices as listed in Amazon.es Website.

[2]Unitary cost prices as listed in Plesk.com Website

Table 8 Standard brandmark SCADA system implementation cost.

Device	Qty	Unit Cost	Import
SENTRON PAC 3200 Power Meter	9	600 € [1]	5,500 €
Meteorological data logger	1	200 € [1]	200 €
OMRON Programmable Logic Controller CJ1M with serial communication CJ1WSCU31, ethernet communication CJ1WETN21, relay output CJ1WOC211 and power source CJ1W-PA205R modules.	1	2,200 € [2]	2,200 €
PLESK Web server annual fee	1	60 € [3]	60 €
CX-Supervisor SCADA system	1	1,500 € [2]	1,500 €
Other	1	200 € [4]	200 €
TOTAL			9,360 €

[1]Unitary cost prices as listed in PCE-instruments.com; [2] Unitary cost prices as listed in Mouser.es Website; [3] Unitary cost prices as listed in Plesk.com Website; [4]Unitary cost prices as listed in Amazon.es Website.

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2.2 A CASCADE HYBRID PSO FEED-FORWARD NEURAL NETWORK MODEL OF A BIOMASS GASIFICATION PLANT FOR COVERING THE ENERGY DEMAND IN AN AC MICROGRID

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A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid

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ABSTRACT

Agriculture and forestry crop residues represent more than half of the world's residual biomass; these residues turn into synthesis gas (syngas) and are used for power generation. Including Syngas Gensets into hybrid renewable microgrids for electricity generation is an interesting alternative, especially for rural communities where forest and agricultural waste are abundant. However, energy demand is not constant throughout the day. The variations in the energy demand provoke changes in both gasification plant efficiency and biomass consumption. This paper presents an Artificial Neural Network (ANN) based model hybridized with a Particle Swarm Optimization (PSO) algorithm for a Biomass Gasification Plant (BGP) that allows estimating the amount of biomass needed to produce the required syngas to meet the energy demand. The proposed model is compared with two traditional models of ANNs: Feed Forward Back Propagation (FF-BP) and Cascade Forward Propagation (CF-P). ANNs are trained in MATLAB software using a set of historical real data from a BGP located in the Distributed Energy Resources Laboratory of the Universitat Politècnica de València in Spain. The model performance is validated using the Mean Squared Error (MSE) and linear regression analysis. The results show that the proposed model performs 23.2% better in terms of MSE than de other models. The tunning parameters of the optimal PSO algorithm for this application were found. Finally, the model was validated to predict the necessary biomass and syngas to cover the energy demand.

1. Introduction

Today, society highly depends on fossil fuels such as petroleum and derivates, mineral coal, and natural gas, with 76% of the global primary energy consumed coming from these sources [1]. Thanks to their high energy density, fossil fuels have been a powerful driver of social transformation and technological development of the last century, and the continued increase in global energy demand [2]. However, extensive use of these fuels has led the world to an unprecedented increase in environmental problems such as global warming [3,4], and health-related issues derived from pollution and toxicity [5].

Researchers have proposed many renewable energy systems to solve this situation [6,7]. Included are the Hybrid Renewable Energy Systems (HRES) as Microgrids (MG), integrating wind and solar technologies [8–10]. Since MG are complex and nonlinear systems, metaheuristic algorithms are an alternative to solve optimal sizing [11] and to improve power generation and energy demand–supply. Bio-inspired optimization algorithms play an important role in the power exchange problem between MG and utility grid, leading to an increment of the power system resilience. In [12], an Energy Management System (EMS) presents a combination of Fuzzy Inference System (FIS) with Genetic Algorithm (GA) to maximize the profit of power exchange; in [13] power exchange problem studied in a multi MG environment combining a game theory Stackelberg game with a Quasi-oppositional Symbiotic Organism Search Algorithm to improve power exchange.

An essential part of an MG is the Energy Storage Systems (ESS), which could be a battery bank or and Energy Backup Power Generation Systems (EBPGS) fed by fossil fuels to provide power when renewable sources are not available. An efficient alternative to fossil fuels for energy backup systems is biomass-derived fuels to supply power in MG [14].

Biomass is neglected despite being a widespread abundant and a Renewable Energy Source (RES) [15]. Some biomass research is focused on finding biomass-derived gas fuels, as Syngas, for power generation applications [16] combined with other RES in MG systems applications

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2.2.1 Abstract

Agriculture and forestry crop residues represent more than half of the world's residual biomass; these residues turn into synthesis gas (syngas) and are used for power generation. Including Syngas Gensets into hybrid renewable microgrids for electricity generation is an interesting alternative, especially for rural communities where forest and agricultural waste are abundant. However, energy demand is not constant throughout the day. The variations in the energy demand provoke changes in both gasification plant efficiency and biomass consumption. This paper presents an Artificial Neural Network (ANN) based model hybridized with a Particle Swarm Optimization (PSO) algorithm for a Biomass Gasification Plant (BGP) that allows estimating the amount of biomass needed to produce the required syngas to meet the energy demand. The proposed model is compared with two traditional models of ANNs: Feed Forward Back Propagation (FF-BP) and Cascade Forward Propagation (CF-P). ANNs are trained in MATLAB software using a set of historical real data from a BGP located in the experimental microgrid of the Renewable Energy Laboratory at the Polytechnic University of Valencia, Spain. The model performance is validated using the Mean Squared Error (MSE) and linear regression analysis. The results show that the proposed model performs 23.2% better in terms of MSE than de other models. The tunning parameters of the optimal PSO algorithm for this application were found. Finally, the model was validated to predict the necessary biomass and syngas to cover the energy demand.

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

Nomenclature

ANN	Artificial Neural Network
BGP	Biomass Gasification Plant
BGP	Biomass Gasification Plant plus Genset
BP	Back Propagation
c_1	PSO particle personal acceleration coefficient

c_2	PSO particle social acceleration 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
E	Error
EBPGS	Energy Backup Power Generation Systems
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}	Objective Function to be minimized
F_{pro_n}	ANN Propagation Function
GA	Genetic Algorithm
Genset	Internal combustion engine plus synchronous generator
$H_2[\%]$	Hydrogen Percentage
HRES	Hybrid Renewable Energy Systems
ICE	Internal Combustion Engine
LabDER-UPV	Distributed Energy Resources Laboratory of the Universitat Politècnica de València
LHV	Lower Heating Value
M	Biomass flow
MG	Microgrids
MLP	Multilayer-Perceptron
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
$Q_{air_{gasifier}}$	Airflow to the reactor
$Q_{air_{ICE}}$	Airflow to the ICE
Q_{syngas}	Syngas flow
RBF	Radial Basis Function
RES	Renewable Energy Source
T_{env}	Environmental Temperature
T_1	Temperature of the reactor
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
ΔP_{bed}	Fluidized bed pressure drop

2.2.2 Introduction and State of Art

Today, society highly depends on fossil fuels such as petroleum and derivates, mineral coal, and natural gas, with 76% of the global primary energy consumed coming from these sources [54]. Thanks to their high energy density, fossil fuels have been a powerful driver of social transformation and technological development of the last century, and the continued increase in global energy demand [55]. However, extensive use of these fuels has led the world to an unprecedented increase in environmental problems such as global warming [56], [57], and health-related issues derived from pollution and toxicity [58].

Researchers have proposed many renewable energy systems to solve this situation [59], [60]. Included are the Hybrid Renewable Energy Systems (HRES) as Microgrids (MG), integrating wind and solar technologies [61]. Since MG are complex and nonlinear systems, metaheuristic algorithms are an alternative to solve optimal sizing [62] and to improve power generation and energy demand-supply. Bio-inspired optimization algorithms play an important role in the power exchange problem between MG and utility grid, leading to an increment of the power system resilience. In [63], an Energy Management System (EMS) presents a combination of Fuzzy Inference System (FIS) with Genetic Algorithm (GA) to maximize the profit of power exchange; in [64] power exchange problem studied in a multi MG environment combining a game theory Stackelberg game with a Quasi-oppositional Symbiotic Organism Search Algorithm to improve power exchange.

An essential part of an MG is the Energy Storage Systems (ESS), which could be a battery bank or and Energy Backup Power Generation Systems (EBPGS) fed by fossil fuels to provide power when renewable sources are not available. An efficient alternative to fossil fuels for energy backup systems is biomass-derived fuels to supply power in MG [65].

Biomass is neglected despite being a widespread abundant and a Renewable Energy Source (RES) [66]. Some biomass research is focused on finding biomass-derived gas fuels, as Syngas, for power generation applications [67] combined with other RES in MG systems applications [68], [69]. Typical compounds of Syngas are carbon monoxide (CO), hydrogen (H_2) and Methane (CH_4) as energy carriers [70], and because of the partial combustion of biomass in the gasifier, it may also contain appreciable amounts of carbon dioxide (CO_2), nitrogen (N_2) and water (H_2O) [66]. Authors in [71] reviewed on how microgrids integrating syngas generation units improve system resilience to natural disasters and other situations. The Department of Mechanical and Aerospace Engineering at the University of Rome [72] developed an innovative integrated microgrid based on urban waste treatment that enables syngas production intended for small towns where the utility grid may fail, and there is enough urban waste to produce the required syngas. In [73], authors present a method to design an HRES in isolated rural communities in Honduras, considering a syngas power generation unit. They found that adding a syngas gasifier increases the dispatchable power rate when needed.

Beyond experimentation with Syngas gasification plants, researchers need to have models that allow them to understand the dynamics of these systems and the variables involved, and make output predictions to variable inputs [74]. However, mathematical modelling of a Syngas gasification plant is a very complicated and time-consuming task, since it comprises multiple thermal processes and many variables that may affect the mathematical model accuracy [75].

Under this context, bio-inspired algorithms, and specifically Artificial Neural Networks (ANNs), are a powerful tool. ANNs had been widely applied to MG for primary control [76], [77], for prediction [78]–[81], for RES forecast [82] and, for creating black-box models of complex dynamic systems [83]. The tracking of the optimal operating point of a solar photovoltaic (PV) source [84] is achieved by modelling with an ANN part of the controller. Wind Turbine Generator (WTG) maximum power point tracking is achieved using an Adaptative Linear Neuron ANN in [85] by modelling the WTG stator's speed controller. In [86], the authors present a NN model approximation of a DC-DC buck-boost converter to interface a lead-acid battery to a DC-bus. As for the application of ANNs to biomass systems in MG, few works talk about BGP and syngas for power generation. Authors in [87] present a model of a 200 kW_{th} using a dynamic ANN; the presented model estimates the overall behaviour of the biomass gasification process and can estimate output variables bases on new measured data with a maximum 15% estimation error. A Multilayer-Perceptron (MLP) and a Radial Basis Function (RBF) ANNs were used and compared to model hydrogen-rich syngas produced from methane dry [88]; results showed that the MLP-based ANN had a better performance in predicting H_2 yield, CO yield, and CH_4 and CO_2 conversions. In [89], authors revealed Syngas for power generation using a Hybrid Thermoelectric Generator (TEG),, a Back Propagation (BP) ANN is used to estimate the open-circuit voltage and maximum power output at the hot-side of the TEG. ANN model is applied to investigate the production of methanol from syngas [90]. A two-inputs seven-hidden layer one-output BP ANN is used in [79] to predict Syngas composition product of palm oil waste gasification showing a suitable approach between experimental and predicted values. In [91], the authors proposed a model for the Prediction of pyrolysis products using eight inputs, one hidden layer, and three outputs ANN. As shown in the literature review, ANNs are applied in various MG, but few in biomass for power generation, with most of the research, focused on the characterization of Syngas or the process itself. We have found no work-related to the coverage of energy demand using syngas and its related biomass gasification process.

This paper aims to provide a reliable ANN-based model of a Biomass Gasification Plant (BGP) for covering the energy demand in an MG using syngas. To accomplish this, a cascade hybrid Feed Forward PSO (FF-PSO) ANN-based model is proposed for predicting syngas and biomass required for a specific energy demand curve. An in-depth analysis of the proposed model compared to a Feed-Forward Back Propagation (FF-BP) ANN and a Cascade-Forward Propagation (CF-P) ANN algorithm is carried out. The validation of the results uses the BGP experimental data at the Renewable Energies Laboratory at the Universitat Politènica de València (LabDER-UPV), Spain.

The organization of this paper is as follows. Section 2 deals with the method, explaining the experimental setup, the presentation of the proposed ANN model, and the training scenarios; Section 3 shows the simulation and experimental results and validation; and, finally, Section 4 summarizes the conclusions of the presented work.

2.2.3 Methodology and Proposed Model

The methodology followed to create and validate the proposed ANN-based model for the BGP system comprised experimental data gathering, modelling, simulation, and validation. The overall methodology is divided into three crucial stages, as Figure 20 shows.

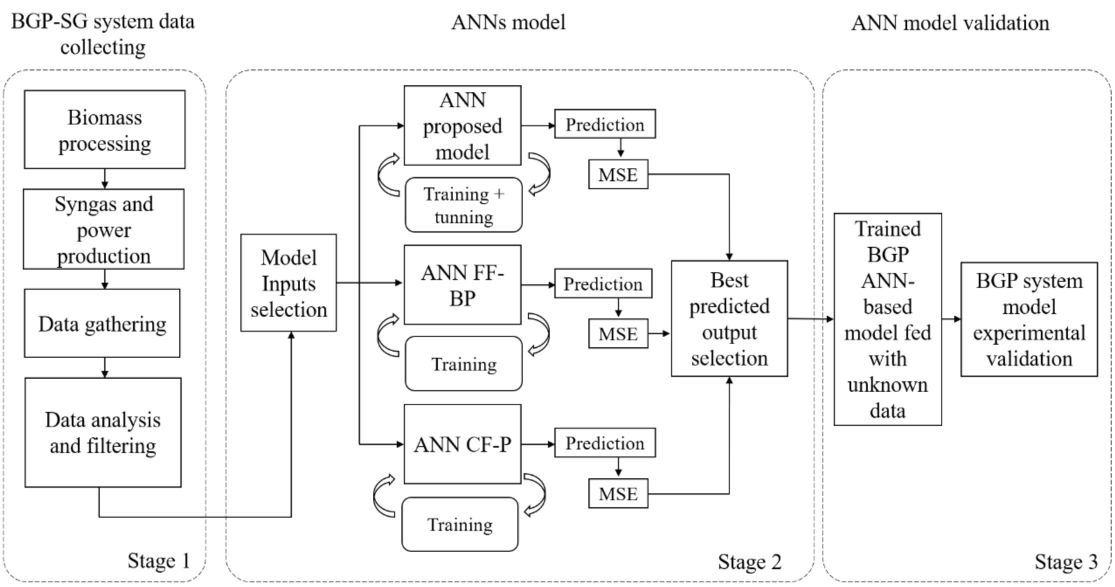


Figure 20 Overall methodology stages for the ANN model design and validation.

As depicted in Figure 20, Stage 1 runs the BGP using empirical input parameters to meet a specific energy demand curve; then, data collection is performed, filtered, and analyzed to select an adequate input parameter for the ANN model.

In Stage 2, three ANN models are trained using input parameters from Stage 1. The proposed ANN-based model is designed to combine a PSO algorithm with a Feed-Forward (FF) ANN to find optimum ANN weights during its training to reduce Mean Squared Error (MSE) between predicted and real experimentation data. The second model is an FF-BP ANN model designed using MATLAB NNTool, and the third model is a CF-P ANN model also designed using MATLAB NNTool. The number of simulations required for each model depends on both the system dynamics and performing each algorithm for error reduction based on training criteria and parameters for each ANN, so an initial scan for each model is required to determine the best adjustment parameters for training the ANN models. After predicted outputs of the ANN models are obtained and evaluated in terms of MSE, the best model is chosen.

Stage 3 is model validation using non-training data. For this purpose, an energy demand curve is fed to the ANN model; then, the model predicts the syngas, biomass, and airflow required by the generator to meet the energy demand. Validation is carried out using the suggested biomass and airflow into the experimental BGP, allowing a real-time approach for biomass required to produce enough syngas for energy demand covering inside an MG. The tests were conducted on an experimental MG located at Universitat Politècnica de València.

2.2.3.1 Biomass gasification plant

The BGP system is located at the Laboratory of Renewable Energy of the Universitat Politècnica de València, in Spain. (see Figure 21). The entire system comprises a reactor, a gas cleaning system, a gas cooling system, a vacuum pump, and auxiliary elements with its control devices. The plant can process from 7 to 10 kg/h of biomass to produce 27 to 33 Nm^3/h at rated power. The gasification system is composed of a 50 kW_{th} gasifier and a 10 kW_e. The flow of syngas goes from. The biomass gasification technology selected is based on the bubbling fluidized bed. Table 9 and Table 10 show the fundamental characteristics of the gasification plant and its generator.

(a)

(b)

Figure 21 BGP at the LabDER-UPV (a) front and (b) back view.

Table 9 Main features of the gasification system.

Description	Feature
Biomass gasification type	Bubbling fluidized bed
Biomass reactor dimensions	Diameter: 106 mm, Height: 155mm
Fuel type	Wood chips (10-15 mm)
	Pellets (6 mm diameter, 15-25 mm length)
Biomass input @ 10%	6 – 13 kg
Biomass flow at power rating	10,5 kg/h
Syngas Low Heating Value (LHV)	5 – 5.8 MJ/m^3
Efficiency at the power rating	70 - 85 %
Syngas production	13 – 33 Nm^3/h

*Adapted from [68], [92].

Table 10 Main features of the Genset.

Description	Feature
Brand	FG Wilson Generator Set
Model	UG14P1
Power rating	10 kW (Natural gas), 8,7 (syngas)
Velocity	1,500 rpm
Compression ratio	8.5:1
Voltage and Frequency	230 V AC, 50Hz

*Adapted from [68], [92].

describes the principal components of the BGP control system. Figure 22 shows the working process of the BGP. The selected inputs for training the ANN, showed in Figure 22, depending on the power generation's performance during the syngas production process from the biomass according to the experimental tests carried out.

Table 11 Main components of the control panel system.

Description	Device
Two power meters	Siemens Sentron PAC3200
Power supply @ 240 VAC	Omron CJ1W-PA202
Programmable Logic Device (PLC)	Omron CJ2M-CPU11
Communication module	Omron CJ1W-SCU31
Six-input thermocouple module	Omron CJ1W-TS561
Sixteen digital outputs module	Omron CJ1M-OD212
Variable frequency drive	Omron V1000
HMI touch screen	Omron NS5-SQ10B-V2
Two modules with eight analog inputs	MAC 35080

*Adapted from [68], [92].

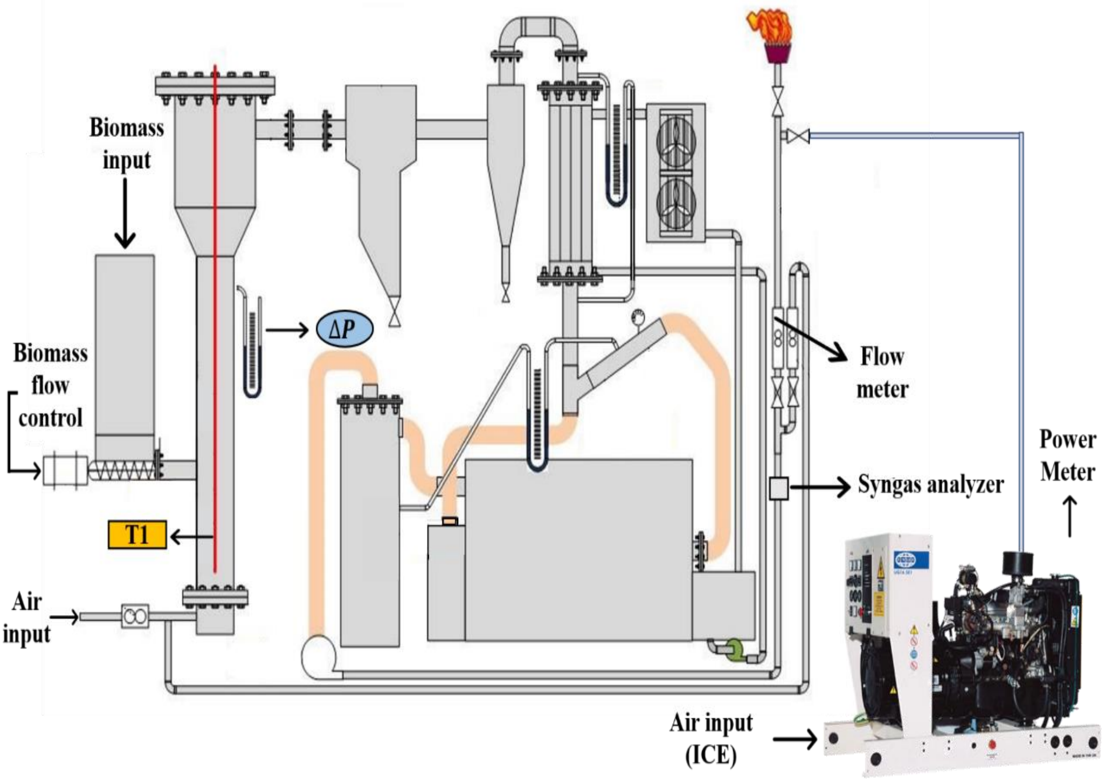


Figure 22 Biomass Gasification Plant and overall diagram.

2.2.3.2 Proposed Artificial Neural Network Model

An ANN is a computational bioinspired algorithm based on imitating learning and memorizing a biological brain's capabilities and neural network synapsis. Thanks to the increase of computation power, ANN algorithms are currently an interesting alternative for predictive modeling and control because of their robustness and handling capability for complex nonlinear relationships on dynamic systems. ANNs must be trained before their use, for this purpose, a set of input training data feeds the Neural Network. The information is processed to get the target data set [93]. When dispersion between target data and real data is small, the ANN is said to be trained and ready to use. An ANN's performance depends on the training procedure and the resulting neuron weights and bias inside its layers [94]. This paper proposes a novel Biogas Gasification (BGP) model using a cascade set of ANNs, each one combined with a PSO algorithm to find optimal neuron weights for each ANN of the model. Figure 23 indicates the input and output of every ANN, in the cascade set of ANN-based model for the BGP.

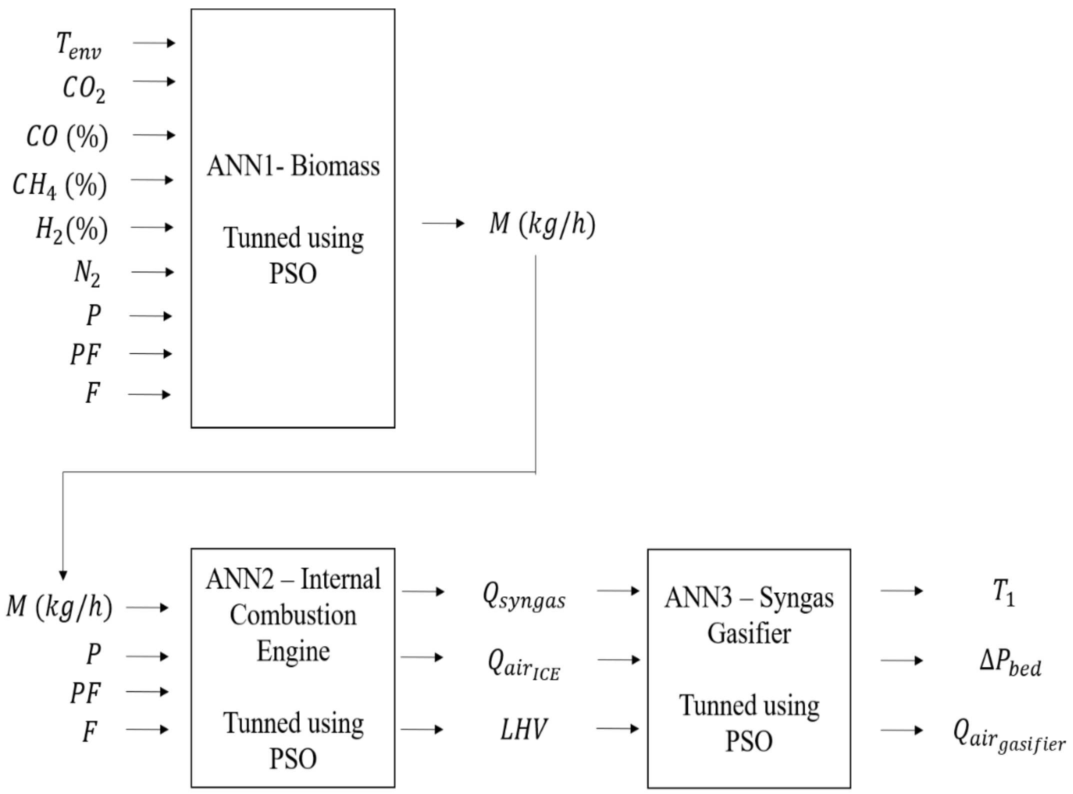


Figure 23 Proposed cascade ANNs PSO tunned model for the BGP.

The proposed ANN-based architecture allows the model to be flexible enough to know just one set of predicted values and intermediate values related to BGP subsystems. The proposed ANN training algorithm uses the PSO algorithm to find optimal neuron weights values, so the MSE between the target and predicted data is minimized. PSO is a bio-inspired optimization algorithm based on animal species' collective intelligence to search, find, and exploit resources [95]. Since neuron weight adjusts during ANN training is a combinatorial problem, PSO can be integrated. Figure 24 illustrates the integration of PSO to an FF ANN.

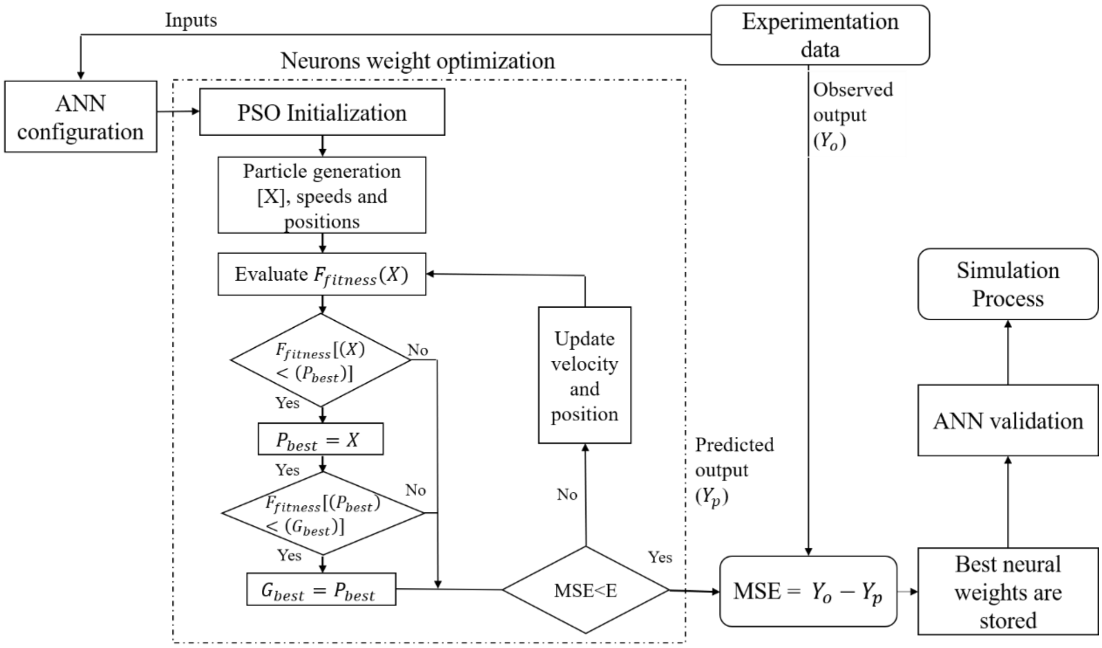


Figure 24 PSO Feed-Forward ANN hybridized model.

The input layer of each ANN of the cascade model comprises one neuron for each variable at the input layer. After the ANN is first configured, the PSO is initialized with a random particle population, and then optimization begins.

Optimization variables are ANN weights, represented by the PSO particles, then the performance of the configuration is evaluated using the fitness function whose objective function is to minimize MSE between target and predicted values of the ANN, MSE minimizing is set to an Error (E) stop criteria for the optimization algorithm, the value of this stop criteria depend on the nature of the training and target values of the ANN.

The proposed FF ANN is suitable for complex dynamic system modeling and prediction. Layer inside ANN are interconnected via links, and the strength of this link between neuron i and j is defined as weight $w(i,j)$, that must be optimized by the PSO during training. The weighted sum of propagation functions (1-3), determined by inputs in the neurons, is transformed into an activation function (4-6) for the next layer. In that sense, the propagation function of the ANN can be modeled as:

$$ANN_1 = F_{pro_1}\left(o_{i_1}, o_{i_2}, \dots, o_{i_n}, w_{i_1,j}, w_{i_2,j}, \dots, w_{i_n,j}\right) \tag{1}$$

$$ANN_2 = F_{pro_2}\left(o_{i_1}, o_{i_2}, \dots, o_{i_n}, w_{i_1,j}, w_{i_2,j}, \dots, w_{i_n,j}\right) \tag{2}$$

$$ANN_3 = F_{pro_3}\left(o_{i_1}, o_{i_2}, \dots, o_{i_n}, w_{i_1,j}, w_{i_2,j}, \dots, w_{i_n,j}\right) \tag{3}$$

Where $(o_{i_1}, o_{i_2}, \dots, o_{i_n})$ are the weighted output values of the related propagation function F_{pro_n}. The activation function of the ANN is defined by:

$$A_1(t) = F_{act_1}(ANN_1(t), A_1(t-1), \Phi_1\ ) \tag{4}$$

$$A_2(t) = F_{act_2}(ANN_2(t), A_2(t-1), \Phi_2\ ) \tag{5}$$

$$A_3(t) = F_{act_3}(ANN_3(t), A_3(t-1), \Phi_3\ ) \tag{6}$$

Where F_{act_n} is the activation function for each ANN of the proposed model, the network input is $ANN_1(t)$ and the previous activation status is $A_1(t-1)$. The dispersion between target and predicted data depends on the assigned neuron weights inside de ANN. For this purpose, the PSO algorithm is integrated into the proposed model.

Each of the particles of the PSO algorithm represents a neuron weight inside the ANN; these particles have their position, velocity, and acceleration during the search of the optimal solution, the best ANN weights combination so MSE between target and predicted values measured in terms of the MSE. Optimization variables are defined by the vector X_i in (7).

$$X_i = \left[w_{i_1,j}, w_{i_2,j}, \dots, w_{i_n,j}\right] \tag{7}$$

Where $w_{i_n,j}$ are the ANN weights to be optimized for each ANN, and the objective function (8) of the PSO algorithm is:

$$f_{min} \rightarrow \frac{\sum_{n=0}^{N}\left(o_{target} - o_{predicted}\right)}{N} \tag{8}$$

Where o_{target} is the target output value for the ANN training and $o_{predicted}$ is the predicted output value by the ANN model.

The particle for each variable with the best fitness function of all algorithm iterations is called to be the best global g_{best}, and the best result of fitness function evaluated over each particle is called personal best p_{best}. As algorithm iterations progress position will vary, their velocity will be accelerated, pointing to the best solution (9).

$$v_n = w * v_n + c_1 rand(x) * \left(g_{best,n} - x_n\right) \tag{9}$$

Being v_n the updating of particle speed, w is the inertia factor and c_1 and c_2 are acceleration constants.

2.2.3.3 Simulation and Training

All three ANN models were trained with the same data set. The training data set was obtained from experimental measurements on the described BGP. In total, 3,408 records were used for each variable.

For an ANN training process, the correct choice of input variables, considering their interrelationship and affectation to the system's output, wanted to be predicted for plant modelling. The details of the ANNs models simulated are presented in Table 12.

Table 12 Parameters used for the ANNs models.

Details	**FF-PSO**	**FF-BP**	**CF-P**
Type of ANN	Feed Forward Neural Network	Feed Forward Neural Network	Cascade Forward Neural Network
Training Algorithm	Particle Swarm Optimization	Back Propagation	Propagation
Particle Population	10 – 1000	-	-
C1	1.5 – 2.5	-	-
C2	1.5 – 2.5	-	-
Function for performance	MSE	MSE	MSE
Number of Input Layer	4 – 9	4 – 9	4 – 9
Number of Hidden Layer	1	1	1
Number of Hidden Neurons	1 – 100	1 – 100	1 – 100
Learning Iterations	1000	1000	1000

* Taken from [96].

Each ANN model was simulated and tested under different parameters to find the best configuration for each one of them. The training algorithm for each model aims to reduce the error of prediction, adjusting ANN weight, and bias. The performance of the ANN models is measured by the MSE (10), given as,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{predicted} - Y_{target}\right)^2 \tag{10}$$

Where $Y_{predicted}$ is the output from the ANN, Y_{target} is the experimental data, and N is the number of samples.

Since this work aims to get a model of a BGP using a cascade architecture of a set of ANNs to cover energy demand in an MG, the ANNs inside the model must be trained considering the energy demand curve from the experimental MG. Figure 25 shows the energy demand profile for input data used for training the three different ANN algorithms (FF-BP ANN, CF-P ANN, and the proposed PSO-FF ANN) for evaluation and subsequent choice of best for use.

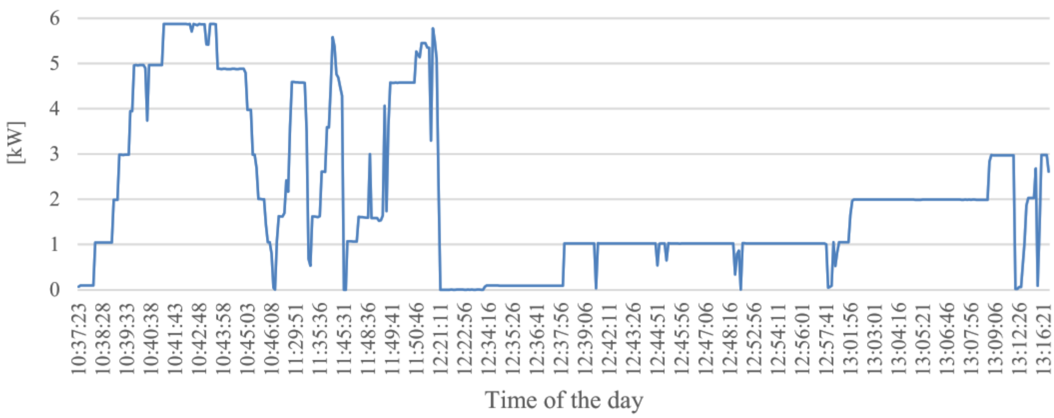


Figure 25 Energy demand curve used for training the cascade ANN-based model of the BGP.

The expected outputs of the model are the best M $[{}^{kg}/_{h}]$ of biomass required to produce a Q_{syngas} to be fed into the Internal Combustion Engine (ICE) combined with both airflows of the gasifier and the ICE to generate enough power for energy demand in an AC Microgrid.

2.2.4 Results and Discussion

An ANN-based model for a BGP was developed to estimate biomass required, syngas production, and power generation to cover the energy demand in an AC microgrid. The proposed model comprises a set of three ANNs in a cascade configuration. Prediction of biomass flow (*M*) is carried out for the first ANN inside the model; the second ANN predicts the flow of syngas (Q_{syngas}), the flow of air required by the Genset ($Q_{air_{ICE}}$), and the lower heating value of the syngas (*LHV*); and finally, the temperature inside the reactor (T_1), the bed reactor pressure drop (ΔP_{bed}), and the airflow required by the gasification plant ($Q_{air_{gasifier}}$) are estimated by the third ANN. The proposed model's performance is tested using the MSE for three different training algorithms: FF-PSO, FF-BP, and CF-BP, for each ANN inside the model. With the FF-PSO training algorithm, different values of particle populations, social c_2 and personal c_1 factors were evaluated. 215 simulations were performed to find the optimal ANN configuration of each training algorithm compared in this work. The comparison between the best ANN of each training algorithm is presented in Table 13. For all predicted variables, the lowest MSE values are obtained using the proposed FF-PSO ANN algorithm and the closest to the unitary R-value results.

Table 13 Comparison of MSE and linear regression analysis for best training algorithm results simulated for the ANN-based model.

	FF-PSO		**FF-BP**		**CF-P**	
	MSE	R	MSE	R	MSE	R
$M\ (kg/h)$	0.8198	0.8278	0.9258	0.8105	0.9277	0.8219
Q_{syngas}	0.3464	0.9865	0.5463	0.9710	0.5466	0.9798
$Q_{air_{ICE}}$	45.1225	0.6503	50.6902	0.6430	50.9046	0.6426
LHV	26705	0.7280	29439	0.6757	29491	0.7124
T_1	342.5776	0.6417	497.3452	0.5595	497.1061	0.5536
ΔP_{bed}	1.5659	0.7728	1.9691	0.7210	1.9789	0.7240
$Q_{air_{gasifier}}$	0.4495	0.9531	0.6442	0.9504	0.6451	0.9367

* Taken from [96].

An exploration of various setting up parameters for each ANN training algorithm was done. The number of neurons inside the hidden layer was varied in values from 3, 10, and 100 for the FF-PSO, FF-BP, and CF-P ANNs training algorithms.

For the FF-PSO ANN algorithm, besides the number of neurons, it was also tested under different PSO algorithm configurations varying particle population with values of three to four times the dimension of the problem as suggested in other works about PSO algorithm performance using small populations [97]–[99].

However, little attention has been paid to optimal PSO configuration for real-world problems [100], and therefore, for biomass-related problems.

An exploration of the PSO performance as an ANN training algorithm is carried out using particle populations of 10, 100, 600, and 1000. The best FF-PSO ANN results were obtained for coefficients c_1 and c_2 values of 1.5 and 2.5 respectively being consistent with other authors findings in different fields of PSO applications [98].

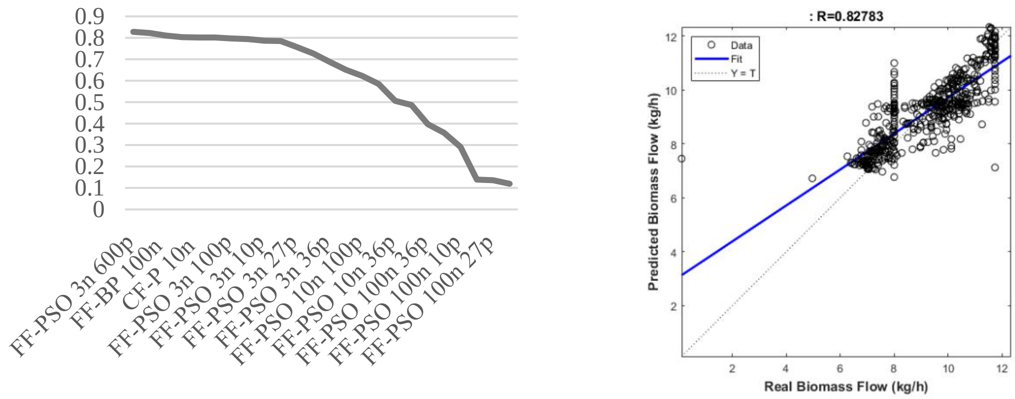
Table 14 presents a summary of the configurations with best performance for each ANN training algorithm tested.

Table 14 Best ANN training algorithm configurations.

	MSE	R	Input Neurons	Hidden Layer Neurons	Population (only for PSO)
FF-PSO					
$M\ (kg/h)$	0.8198	0.82783	9	3	600
Q_{syngas}	0.3464	0.98646	4	3	100
$Q_{air_{ICE}}$	45.1225	0.6503	4	10	1,000
LHV	26705	0.7280	4	10	1,000
T_1	342.5776	0.6417	3	10	600
ΔP_{bed}	1.5659	0.7728	3	10	600
$Q_{air_{gasifier}}$	0.4495	0.9531	3	3	1,000
FF-BP					
$M\ (kg/h)$	0.9258	0.81045	9	100	-
Q_{syngas}	0.5463	0.97995	4	100	-
$Q_{air_{ICE}}$	50.6902	0.6430	4	100	-
LHV	29439	0.6757	4	100	-
T_1	497.3452	0.5595	3	10	-
ΔP_{bed}	1.9691	0.7210	3	3	-
$Q_{air_{gasifier}}$	0.6442	0.9504	3	10	-
CF-P					
$M\ (kg/h)$	0.9277	0.82194	9	100	-
Q_{syngas}	0.5466	0.97976	4	10	-
$Q_{air_{ICE}}$	50.9046	0.6426	4	100	-
LHV	29491	0.7124	4	100	-
T_1	497.1061	0.5536	3	3	-
ΔP_{bed}	1.9789	0.7240	3	100	-
$Q_{air_{gasifier}}$	0.6451	0.9367	3	100	-

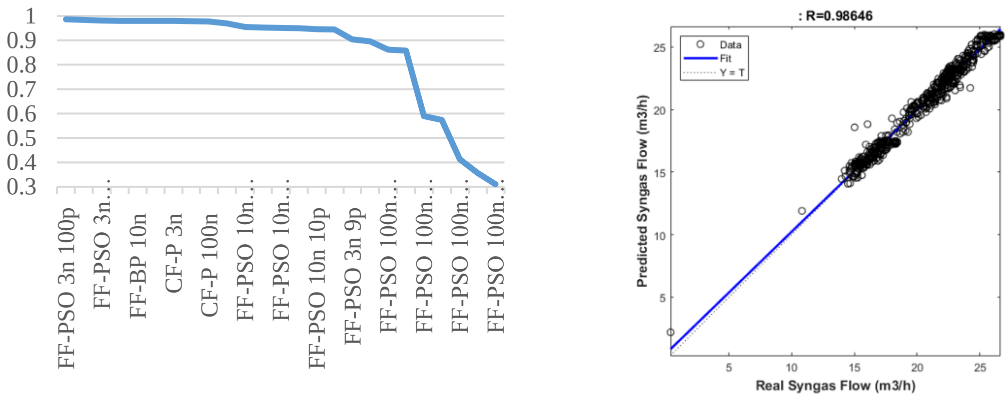
* Taken from [96].

As observed in Table 14, the best FF-PSO algorithm performances are obtained for the particle population between 600 and 1000 and three to ten hidden layer neurons; while both for the FF-BP and CF-P best results are achieved for 100 hidden layer neurons in most of the cases, but always with a more significant MSE value compared to the proposed FF-PSO training algorithm. The *R* value evolution for different ANNs configurations training tests and the best *R* plot for biomass flow, syngas flow, ICE inlet airflow, *LHV*, gasifier temperature, fluidized bed pressure drop, and gasifier airflow are shown from Figure 26 to Figure 32.



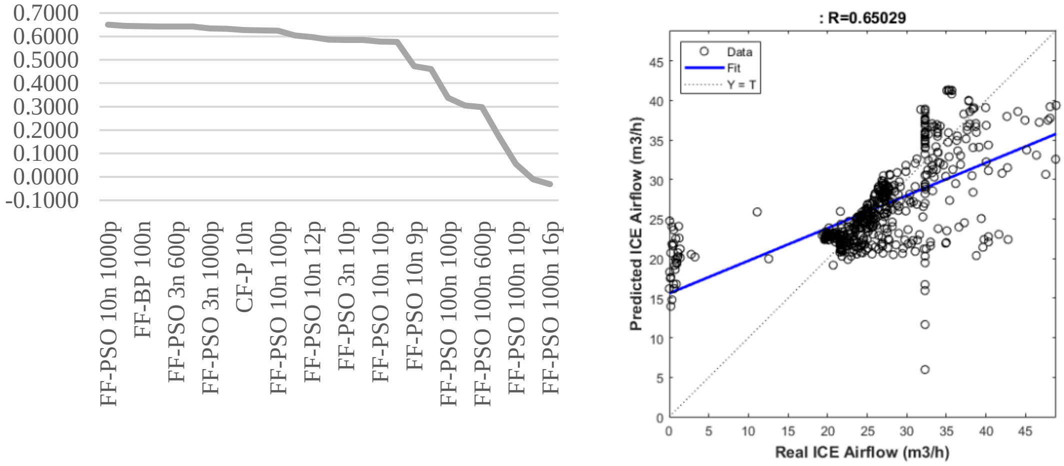
(a) (b)

Figure 26 (a) Linear regression *R* value evolution of Biomass flow for best ANN training algorithm results and (b) best ANN linear regression plot.



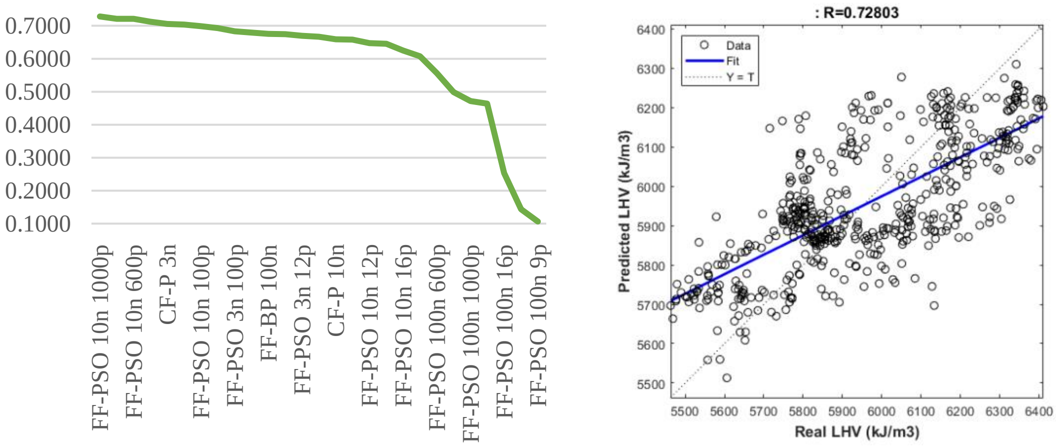
(a) (b)

Figure 27 (a) Linear regression *R* value of Syngas flow for best ANN training algorithm results and (b) best ANN linear regression plot.



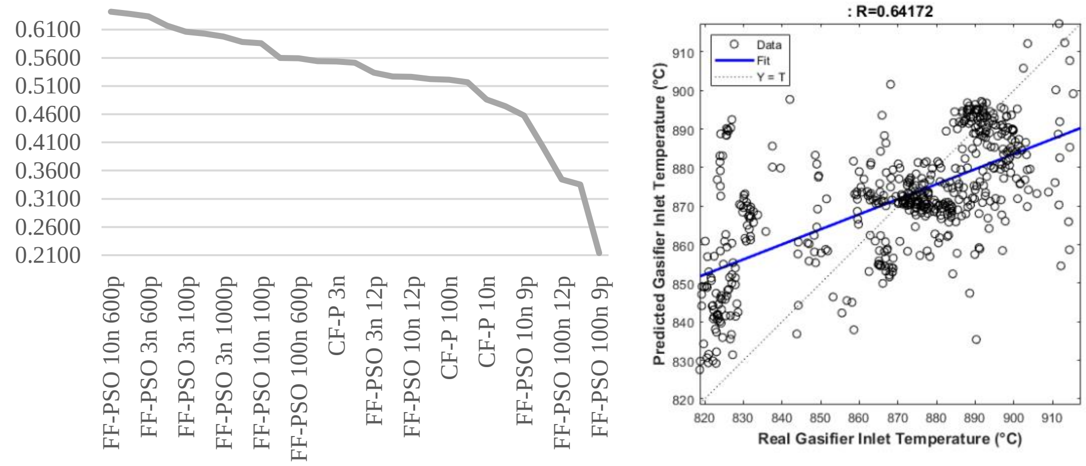
(a) (b)

Figure 28 (a) Linear regression *R* value evolution of ICE inlet airflow for best ANN training algorithm results and (b) best ANN linear regression plot.



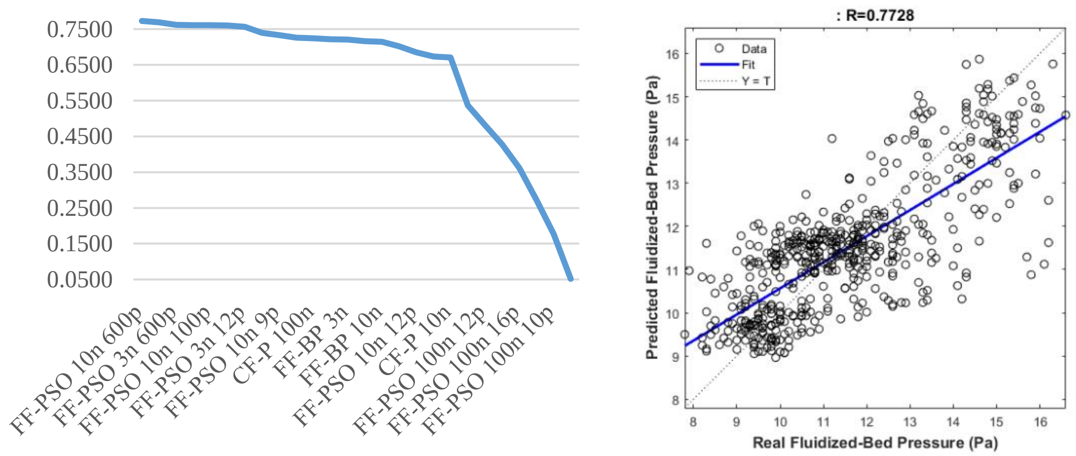
(a) (b)

Figure 29 (a) Linear regression *R* value evolution of LHV for best ANN training algorithm results and (b) best ANN linear regression plot.



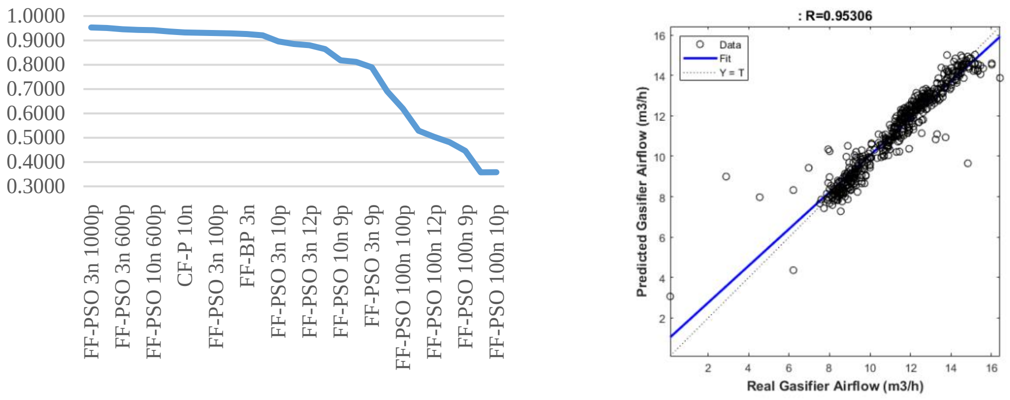
(a) (b)

Figure 30 (a) Linear regression *R* value evolution of Gasifier Inlet Temperature for best ANN training algorithm results and (b) best ANN linear regression plot.



(a) (b)

Figure 31 (a) Linear regression *R* value evolution of Fluidized-Bed Pressure for best ANN training algorithm results and (b) best ANN linear regression plot.



(a) (b)

Figure 32 (a) Linear regression R value evolution of Gasifier airflow for best ANN training algorithm results and (b) best ANN linear regression plot.

High rates of dispersion on linear regression observed in variables (Figure 28 to Figure 31) are caused because of different variable scales used during the process for the individual analysis. The best predictions for each of the variables analyzed are summarized in Table 15.

Table 15 Best predictions for the variables analyzed using the FF-PSO model.

	Best MSE, FF-PSO	**MSE Improvement (FF-PSO respect to FF-BP)**	**MSE Improvement (FF-PSO respect to CF-P)**
$M\ (kg/h)$	0.8198	11%	12%
Q_{syngas}	0.3465	37%	37%
$Q_{air_{ICE}}$	26705	11%	11%
T_1	342.5776	31%	31%
ΔP_{bed}	1.5659	20%	21%
$Q_{air_{gasifier}}$	0.4495	30%	30%

A comparison between the biomass flow and Syngas flow predicted by the best ANN of each type of training algorithm is shown in Figure 33 and Figure 34, respectively. It can be seen how ANN trained with the proposed FF-PSO algorithm performs better than ANN trained with FF-BP and CF-P.

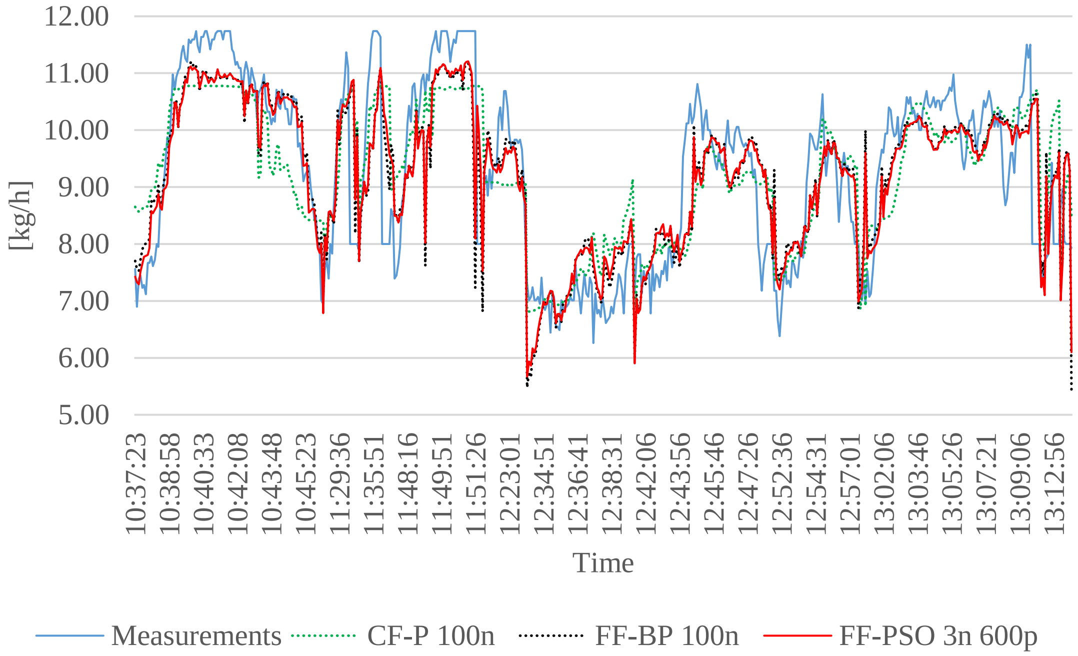


Figure 33 Comparison between best training ANN algorithms and measured data for Biomass flow.

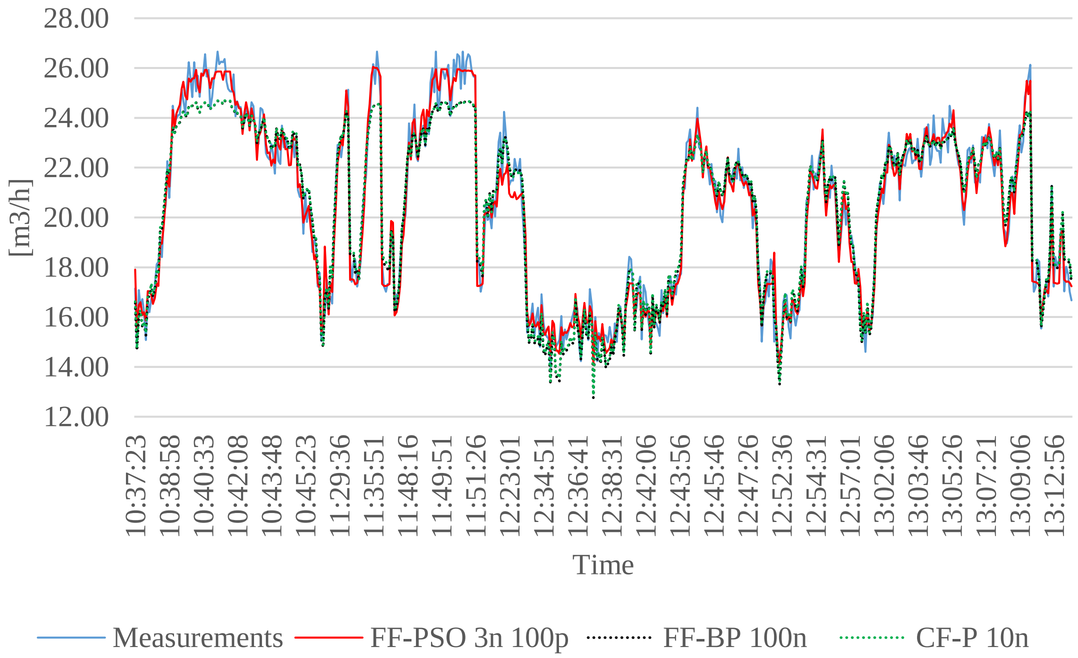


Figure 34 Comparison between best training ANN algorithms and measured data for Syngas flow.

Because of the followed methodology, after tunning and comparing three different training algorithms for the BGP ANN-based model, the ANN-PSO algorithm is chosen, and its best configuration. Figure 35 presents the predicted biomass and syngas' predicted values, using the best algorithm configuration, for the corresponding energy demand curve.

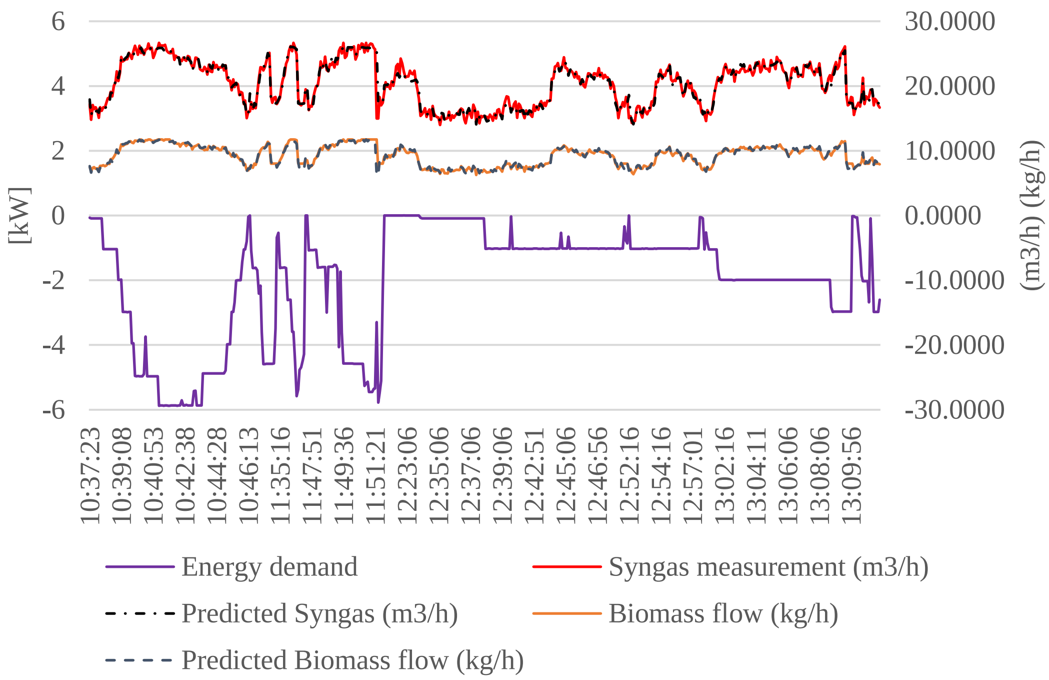


Figure 35 Biomass and Syngas flow required for Energy Demand Covering obtained for the best FF-PSO ANN Training Algorithm.

After the evaluation of the three ANN-based models for the BGP system, the ANN-PSO algorithm was selected as the best training algorithm for this application. The ANN-PSO algorithm got the lowest MSE values (See Figure 35). The results obtained employing the ANN-based model through the proposed FF-PSO were also satisfactory.

The ANN-PSO model was validated to predict biomass and syngas flows required to cover energy demand from an experimental MG. Figure 36 presents the power generation plots, and consumption obtained during testing.

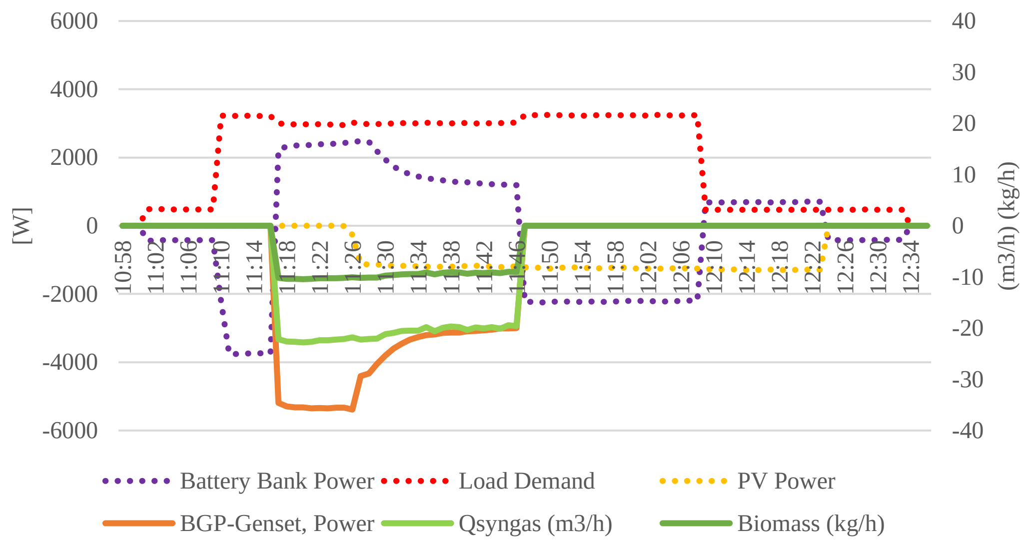


Figure 36 Energy Demand, required biomass, and produced Syngas and Power Plots of MG experimental scenario.

The power produced by the BGP can be predicted and decomposed in the required biomass flow $({kg}/{h})$ and the produced syngas flow $({m^3}/{h})$ used to feed the ICE. The ANN-based model proposed by this methodology can allow a real-time estimation of both the syngas required by the ICE and the biomass required for the BGP to cover the energy demand of the MG.

2.2.4.1 Discussion

In this article, a novel ANN-based model applied to a BGP system has been presented and validated. Since ANNs inside the model need to be trained, three different ANN training algorithms were evaluated: FF-PSO, FF-BP, and CF-P. Training algorithms performance has been measured using MSE, under different ANN configurations: varying number of hidden layers neurons; and different PSO configuration parameters for the FF-PSO, varying population size from 9 to 1000, and $c_1$and c_2 coefficients were varied from 1.5 to 2.5 values. An experimental MG provided the energy demand curve to be supplied into the proposed ANN-based model to predict, as main model outputs, the required biomass flow M and syngas flow Q_{syngas} to cover the energy demand. The cascade architecture of the model also allows the prediction of airflow $Q_{air_{ICE}}$ at the inlet, the LHV, the temperature T_1 at the gasifier inlet, the pressure ΔP_{bed} at the fluidized bed and the airflow $Q_{air_{gasifier}}$ of the gasifier. The evaluation of these algorithms showed that the FF-PSO proposed for the ANN-based model has the best performance, with an MSE an average for all variables prediction of 23.3% lower than the obtained using the FF-BP and CF-P and better linear regressions values.

The model was validated using real data of an experimental MG. The results of the experimentation allowed us to estimate the biomass and syngas flow required to produce the power generation needed. The reached ANN-based model can be applied in a real-time approach to control and manage the BGP.

As a general conclusion, the presented ANN-model applied to a BGP and the proposed FF-PSO algorithm showed to solve model dynamic Power Generation systems. The PSO is an efficient algorithm to train the ANN. The best results were obtained for a few hidden layer neurons (1 to 3), a high number of particle populations (600 to 1000), and standard c_1 and c_2 coefficients (1.5 to 2.5).

In future work is planned to extend the ANN-model to other MG subsystems, allowing effective control for the energy management inside the MG.

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2.3 A SMART RESIDENTIAL SECURITY ASSISTED LOAD MANAGEMENT SYSTEM USING HYBRID CRYPTOGRAPHY

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A smart residential security assisted load management system using hybrid cryptography

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ABSTRACT

A residential load management system equips smart meters (SMs) to measure load utilization at residencies. SM reports electricity usage based on electronic appliances. In this paper, a smart residential load management system is designed by three-fold along with the provisioning of consumer security. Load management encompasses load categorizing by Hopfield neural network, fuzzy-logic based bill payments identification and load state prediction using Markov chain. Residential load is based on three classes: active load, affordable load and inactive load. The estimation of residential load ensures to manage the load at residency either to turn off the load or intimate excess consumption of electricity. The registered consumers of a specific residency are enabled to receive load status by Internet of Things (IoT) devices. SMs at residencies periodically compute the electricity manipulation and those readings are encrypted using hybrid blowfish and elliptic curve cryptography algorithm with considering the behavior information from IoT device and partial key storage assists security, even if the device is theft. This smart residential security assisted load management (SRS-LM) system is developed in network simulator 3 and the results showed improvements in terms of power usage, load power, peak load reduction, total power consumption, power cost and computation time.

1. Introduction

Load management in residential sectors is presented to promote the energy savings of household appliances. Smart Meters (SMs) are devices deployed in a residential environment to monitor electricity usages. The measurements from SMs are temporally varied by the changes in load [1]. Home load management is designed as a decentralised framework that is embedded with SMs [2]. The load is scheduled based on the cost variations from the service provider that comforts the customers. The consumption of electricity depends on the characteristics of every home that defines the constructed structure of it. According to variations in size and counts of the rooms at home, electricity consumption is varied. Among all the available home appliances, some of them consume more considerable energy, whereas others consume comparatively lesser energy [3]. In designing a smart home architecture, the loads are divided based on their utilisation of electricity.

An energy management system in the residential sector is designed to control household appliances to reduce the electricity cost [4]. Considering the load power demand, the payment cost of the customer is determined. This is a potential benefit for the customer, which is attained by designing a two-level residential energy management framework. Increasing electricity demand tends to escalate the energy cost for customers. A smart house management system controls the decisions of household appliances that probably comforts customers [5].

Residential load management system reliability decision based is presented to evaluate customer's participation [6]. Load curtailment function is modelled to minimise the satisfactory level of customer. End-user comfort is provisioned using a heuristic algorithm, i.e. genetic algorithm (GA), for optimal fitness estimation [7,8].

Controlling household appliances is achieved by GA for reducing energy consumption. User activity level is determined from the usage of appliances as ventilation, air conditioning, and others. Peak load at the residency is minimised with the assistance of Quality of Experience (QoE) based on fuzzy logic controller [9]. QoE is adaptively changed

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2.3.1 Abstract

A residential load management system equips smart meters (SMs) to measure load utilization at residencies. SM reports electricity usage based on electronic appliances. In this paper, a smart residential load management system is designed by three-fold along with the provisioning of consumer security. Load management encompasses load categorizing by Hopfield neural network, fuzzy-logic based bill payments identification and load state prediction using Markov chain. Residential load is based on three classes: active load, affordable load and inactive load. The estimation of residential load ensures to manage the load at residency either to turn off the load or intimate excess consumption of electricity. The registered consumers of a specific residency are enabled to receive load status by Internet of Things (IoT) devices. SMs at residencies periodically compute the electricity manipulation and those readings are encrypted using hybrid blowfish and elliptic curve cryptography algorithm with considering the behaviour information from IoT device and partial key storage assists security, even if the device is theft. This smart residential security assisted load management (SRS-LM) system is developed in network simulator 3 and the results showed improvements in terms of power usage, load power, peak load reduction, total power consumption, power cost and computation time.

Keywords: household appliances; IoT devices; smart residential, energy meters; cybersecurity; hybrid cryptography.

2.3.2 Introduction and State of Art

Load management in residential sectors is presented to promote the energy savings of the household appliances. SMs are the special devices that are deployed in residential environment to monitor the electricity usages. The measurements from SMs are temporally varied by the changes in load [101]. Home load management is designed as a decentralized framework that is embedded with SMs [102]. The load is scheduled based on the cost variations from service provider that comforts the customers. In recent days, the increased electronic home appliances, such as air conditioners, dishwashers, refrigerators, washing machine and so on, consume higher energy and hence load management system is developed [103]. The consumption of electricity depends on the characteristics of every home that defines the constructed structure of it. According to variations in size and counts of the rooms at home, the consumption of electricity is varied. Among all the available home appliances, some of them consume larger energy whereas others consume comparatively lesser energy [104]. In designing a smart home architecture, the loads are divided based on their utilization of electricity.

An energy management system in residential sector is designed regarding the control of household appliances to reduce the electricity cost [105]. Considering the load demand, the payment cost of the customer is determined. This is a potential benefit for the customer which is attained by the design of a two-level residential energy management framework. Increasing electricity demand tends to escalate the energy cost for customers. A smart house management system controls decisions of household appliances that probably comforts customers [106].

House distributed state estimation (HDSE) system aggregates measurements from household appliances for determining the states. The peak load at house is controlled by designing an electro-thermal model. The load patterns of appliances are predicted from a nonintrusive load monitoring (NILM) method [107]. Load activities are determined and forecasted based on the individual appliance usage pattern. From the active power profiles, the total power consumed in multiple residencies is estimated. This residential load control system is also presented by the convolutional neural network (CNN) that extracts spatially changing features [108]. Extracted features are evaluated for controlling the load in residential sector. The bin values are estimated in CNN and then the control action is given by greedy strategy.

Power management system is also established by knowledge-based using artificial bee colony (ABC) algorithm for saving energy [109]. To minimize energy consumption, the parameters temperature, air quality, and others are considered. To minimize the power, optimized values are processed in fuzzy to determine error difference. Residential load management system reliability decision based is presented to evaluate customer's participation [110]. Load curtailment function is modelled to minimize the satisfactory level of customer. End-user comfort is provisioned using heuristic algorithm i.e. genetic algorithm (GA) for optimal fitness estimation [111].

Controlling of household appliances is achieved by GA for reducing energy consumption. User activity level is determined from the usage of appliances as ventilation, air conditioning, and others. Peak load at the residency is minimized with the assistance of Quality of Experience (QoE) based on fuzzy logic controller [112]. QoE is adaptively changed based on the estimated power consumption output (Low, Medium and High) from fuzzy logic.

SMs in collecting electricity measurements support IoT applications based on consumers. Security is a challenging issue that is concerned to ensure privacy techniques [113]. Security provisioning is associated with lightweight authentication and cryptography techniques. This SM involved residential sector is subjected to certain vulnerable attacks. In [114], differential privacy is modelled for distinguishing SMs with privacy providence. Additive Homomorphic encryption is used for protecting the smart meter readings. Encrypting the data from SMs is a solution for ensuring security. Flexible data privacy is essential to appropriately decide on the SM reading [115]. Signature-based encryption is constructed at the gateway device in residential environment. SM can collect electricity measurements and encrypt the data for security.

In this paper, a smart residential sector is presented with a secure load management system. Security has become a major concern in this sector which is developed using hybrid cryptography and the load management system identifies peak load. Peak load at residencies are measured by SMs and they are predicted in load management system.

The SM based residential load management and privacy assurance are focused in this paper. Active load i.e. use of household appliances in a residency was monitored and flexibly managed [116]. Based on the household appliances, loads were categorized into two as controllable load and uncontrollable load. Load measurements are analysed by an artificial neural network (ANN) which was operated by the trained data. ANN uses two-layer feed-forward along with back-propagation. The factors that are considered for training are minute based real and reactive power. However, ANN performs faster, it requires a set of data to be trained. An intelligent residential energy management system was proposed to meet the demands of residential buildings [117]. To monitor the load, they were broadly classified into three categories as noninterruptible and nonschedulable loads (NINSLs), interruptible and nonschedulable loads (INSLs), and schedulable loads (SLs). Warning messages are generated if the power consumption exceeds the limit. External battery was operated to manage load and the owner of the residency was not intimated regarding the load peaks.

An Advanced Metering Infrastructure (AMI) was implemented in this work which developed a win-win-win strategy [118]. The proposed strategy operated using an interior-point method constrained particle swarm optimization method and artificial immune system algorithm. Optimization method was enabled for the selection criteria. A hierarchical structure was constructed concerning the service providers. Here the measurements from smart meters are delivered to service providers via AMI. The significant objective of the customer was to minimize the cost based on energy demand. A demand response strategy was developed to schedule residential loads [119]. The loads from residencies were classified into noncontrollable load, interruptible load, adjustable load, and shiftable load. The local historical data were processed with Copula function and Monte Carlo simulation. Then the load setting parameters are defined based on the comfort of every customer, however, it may lead to cause electricity demand.

Demand side management in residential sector was involved into the investigation of electricity tariff and usage of household appliances. The electricity energy cost was mitigated by presenting a tabu search scheduling algorithm for fair billing mechanism [120]. The load was randomly scheduled and based on it, household appliances were operated and while completing the schedules, fair billing is performed. The daytime energy consumption and billing were not minimized since the peak loads were not measured and controlled. A two-phase distributed stochastic linear programming management based cooperation game algorithm was developed for payments and verifying the energy consumptions [121]. Then a cooperative based game algorithm was applied in this work for identifying multiple routes using incomplete information and verifies whether to add or eliminate any agent. The information includes uncertainty as a constraint which considers non-negative vectors. Using this information, a communication graph was constructed which needs to be updated on every minute changes.

A hybrid demand modelling framework was designed to handle both energy management and billing [122]. Mixed customers whose demand was modelled with/without SM were taken into account. The categories of home appliances that are considered are nonshiftable, shiftable and curtailable. Furthermore, the electricity consumption was measured for each category, further cost was estimated separately for customers without SMs and mixed customers (with and without SMs). The minimization of the peak-to-average ratio was significantly discussed in this work. However, the determination of energy consumption without SM is not ensured with accurate measurements and comparatively the time consumption will be higher. In [123], the individual customer's electricity requirement was taken into account, since to assist demand-side management in residential sector. The residential demand-side flexibility by developing a bottom-up load model was constructed.

The proposed Residential Electricity Load Profile simulation and optimization model integrates bottom-up approach with optimization. In this model, the customer exceeding the pre-defined limit of utilization will be applied with an additional penalty. Load profiles were created every week based on the utilization of their household appliances. A demand-side management system was discussed in [124] using weighted and nonweighted approach. Adaptive Neural Fuzzy Inference System (ANFIS) was developed with five consecutive processing layers. The inputs were based on residential loads of natural lighting. This work especially focused on a behavioural pattern which was mostly nonlinear and however it is predicted, it also requires location, lifestyle, and income into load profiles information.

A multi-agent system was presented to resolve the problem of demand response over the electric power system [125]. A new satisfaction function was established to select electricity users based on a decision making. The formulated satisfaction function was based on the difference between the adjusted electricity consumption and the original load. If the satisfaction degree was not selected, then it has no changes in electricity consumption as well as the electricity cost. This was comprehensive and mainly focused only on time difference. Reliability-based energy management system was designed under customer satisfaction model [2]. Customer dissatisfaction model was designed using Kano diagram, in which the satisfaction was given based on attractiveness and the dissatisfaction was given when the demands are not satisfied. The system's peak load was minimized, and the weight values were estimated using fuzzy decision-making method. The customer's electricity cost was mitigated by reducing the peak load.

Load measurements in the residential sector using SMs were also essential to meet security requirements. Involvement of multiple harmful misbehaving particulars into the system, security has become significant. A novel privacy-preserving smart metering scheme was proposed for preventing pollution attacks [126]. This work aided to provide end-to-end security, integrity, and secure data aggregation. A dynamic billing mechanism was also developed by estimating the power consumption. Here, chameleon hash function was used as an identity authentication mechanism to ensure security in smart meters. The billing amount was re-encrypted using the operational center and then returned to customers. Also, an authenticated communication scheme was proposed for ensuring security in SM [127]. Here, a session key was generated while initializing the system and a Merkle hash tree was constructed. The reports are encrypted and compute a value and then transmit the message. The neighbourhood gateway was responsible to authenticate the data received.

In [128], an AMI was resolved by proposing an Identity Management (IdM) and a key-based scheme. Internet of Things was integrated with AMI to mitigate electricity consumption fraud. The proposed system was composed of IoT devices, smart home and Remote Terminal Unit (RTU). A session key was generated and transferred to the electric utility. This session key was composed of token and a serial number, this token number was validated by an authorization server. Later the encrypted value and the token was sent to RTU followed by SM. After receiving the session key, the status measured from SM was delivered to the operator. However, the security designed requires multiple message exchanges and the use of a session key based on static value is not advisable.

The major problems exist in load management, billing strategies and security. Detection of load states was executed using k-means clustering algorithm to group the input signals and then use k-Nearest Neighbor (k-NN) algorithm for classification of load states [18].

Conventional procedure was followed for these methods and the results of classification were based on the clustered data. According to the variation in an input signal, the clustering needs to be re-created for efficient classification and only limited number of clustered were created based on the k-value.

In [129], a low-cost universal smart energy meter (USEM) with demand-side load management was proposed in which the emergency load was previous stored in utility server, based on which the load was managed in this system. The loads were categorized into two categories as heavy load and light load. Here, if the consumer exceeds permitted load then SMS will be sent from the control room to the user. On receiving this SMS, the heavy load must be switched off. In this case, the emergency load condition by a user was not able to satisfy demand at all times, since the electricity production failed to support all the residential customers. Power management was enabled by the design of an adaptive fuzzy logic system integrated with bat algorithm for the prediction of power [21]. This adaptive approach enables to select an optimal path for transmitting information between energy provider and user. In this algorithm, the vector frequency and vector rate are initialized for determining power consumption. First, the loads are recorded with learning vector initialization and then, adaptive vectors were changed for obtaining the best solution. The designed algorithm was able to predict power but failed to manage the load.

Security in residential load management was presented in [22], [130]. The measured SM values were sent to another end, in which security was essential and it was provided by the Unique String Authentication procedure. Android-based application was created for enabling communication between the user and the utility center, in which the status is updated on the user mobile. But here, if the user mobile is lost or stolen, then the status can be viewed by any third person. However, it was equipped with security; they are vulnerable to physical tampering which tends major variations in measured values. Overall, problems defined in this residential sector of load management and security are resolved with the solutions in the proposed SRS-LM system.

2.3.3 Methodology and Proposed LMS

The proposed SRS-LM system is presented to envision and manage load at residential sector along with the provisioning of security for the SM measurements.

2.3.3.1 System model

The SRS-LM system is comprised of IoT devices, load management system, residencies, and the utility grid. Each residency is deployed with multiple household appliances and a SM. SM plays a vital role in SRS-LM system which is responsible to collect electricity usage information from their residency. The designed SRS-LM system consists of N number of residencies as $R_1, R_2, R_3, \ldots\ldots, R_N$ with the corresponding number of SMs represented as $SM_1, SM_2, SM_3, \ldots\ldots, SM_N$ and IoT devices for each residency as $D_1, D_2, D_3, \ldots\ldots, D_N$. The major home appliances that are operated in residency are light, fan, microwave oven, personal computer, air conditioner, refrigerator, water heater, air cooler, water pumps, grinder, dishwasher, and clothes dryer. Household appliances are categorized into three, based on their requirements and energy consumption.

Household appliances in each residency are varied and according to their utilization, the bill payment cost is updated. Based on the household appliances, they are categorized into three as essential appliances, flexible appliances, and optional appliances as shown in Table 16. These categories are split for identifying the load at a residency.

Table 16 SRS-LM Categorize of Appliances.

Category	Type	Household appliances
I	Essential appliances	Light, fan, microwave, oven, personal computer
II	Flexible appliances	Air conditioner, air cooler, water heater, refrigerator
III	Optional appliances	Water pump, grinder, dishwasher

Initially, a three-fold load management is operated using readings from SMs. The three-process handled are Hopfield neural network for load classification, fuzzy logic for payment prediction and Markov chain for identifying states of residency. Lastly, the SM measurements and load updating are accessed by the residency owner via IoT device. The measurements are stored in an encrypted format that is securely accessed only by the IoT user. A hybrid blowfish-ECC algorithm is used for secure data storage. IoT devices are supposed to have the issues as low-memory, low-power and they are resource-constrained. Due to these limitations in IoT, the SRS-LM system makes sure to minimize operations in IoT devices and store partial key for security purposes.

The SRS-LM system gathers data from SMs that are deployed in each residency, and they are processed in the load management system as depicted in Fig. 37. The load management is enabled to compute load status and on the other hand, the bill settlement is also predicted.

2.3.3.2 Load management

Load management is comprised of three major processing as load category classification, load status prediction, and bill payment determination. Bill payment and load status prediction are simultaneously performed.

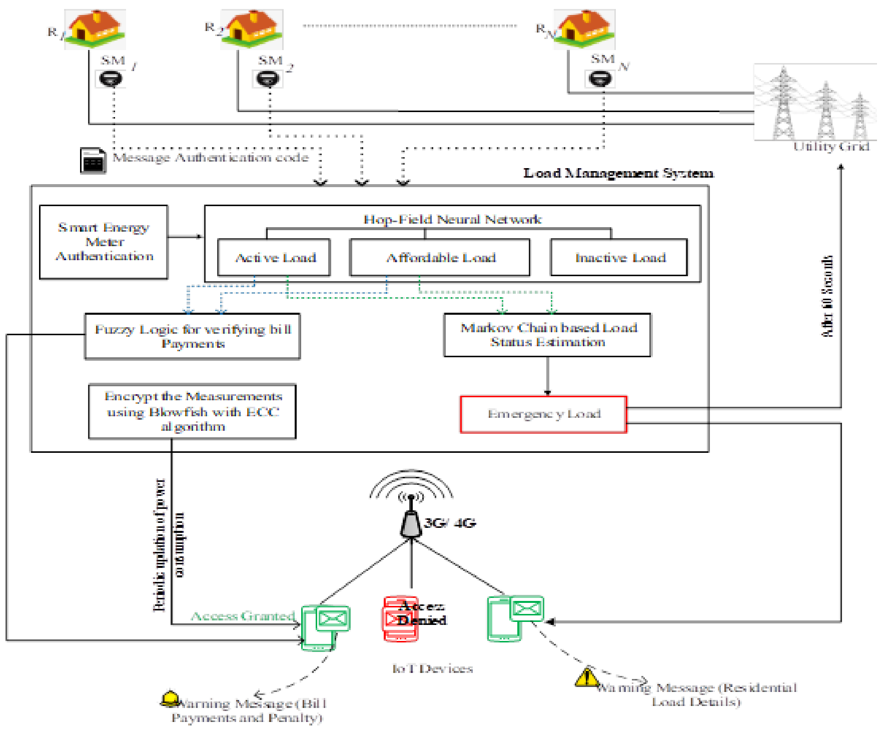

Figure 37 Proposed SRS-LM system model.

The output from this system is updated and in case of a warning message, they are intimated to the user's IoT device. This three-fold load management system is operated using Hopfield neural network, fuzzy logic, and Markov chain. The working of these three blocks for a peculiar process is detailed. The load management system initially authenticates the SM using its Identity (ID) and secret value (s_e). Using these two constraints a message authentication code (MAC) is generated and only after authentication of SM, the further load management process is performed. This MAC is dynamically generated during the submission of SM measurements. Let R_1 having SM_1 with S_{Id1} and s_{e1} as secret value. The MAC value is expressed as:

$$MAC_{SM} = S_{Id1} \oplus s_{e1} \tag{1}$$

The generated MAC_{SM} is exchanged and verified, then for submission of next measurements the MAC is supposed to be as follows:

$$MAC_{SM} = S_{Id1} \oplus (s_{e1} + 1) \tag{2}$$

This computation is simpler and so it is determined by the SM and after completion of authentication, their measurements are analyzed by load management system.

2.3.3.3 Hopfield neural network

Hopfield neural network is one of the types of ANN which is encompassed of nodes on a single layer. The nodes in Hopfield neural network are updated synchronously by clock time variations. The nodes participating here exist with connectivity based on the determined weight values between the connected nodes.

Hopfield neural network uses the measurements from SM as input and classifies the load into active, affordable and inactive. The feedback loops formed in this network reflects its performance in enriching learning capability. This is efficient in solving complex computational problems. The household appliances used in three categories are depicted in the above section 4.1. The Hopfield neural network is designed with a single layer of nodes that are connected with other nodes as feedback connections which assists to redirect the output into the input. Here the number of nodes, inputs, and outputs are equal, in this SRS-LM system the total number of residential as $R_1, R_2, R_3, \ldots\ldots, R_N$ nodes are constructed. The nodes are binary threshold nodes since they are served as a content addressable memory system. According to the arrival of input, it defines a corresponding weight value. The weight value of the received input is determined from individual residential measurement which is formulated based on the weight connectivity and state of the node. The weighted sum of the nodes I is estimated from the following expression:

$$I_i = \sum_{j=1}^{N} w_{ij} s_j \tag{3}$$

Where w_{ij} represents the connectivity weight exists between i and j, then s_j is the state of the node j. Training in Hopfield neural network is handled by using learning rules, in SRS-LM a Storkey learning rule is applied for better error minimization. The mathematically defined Storkey learning rule is formulated as follows:

$$w_{ij}^{0} = 0 \quad \forall i, j \tag{4}$$

$$w_{ij}^{k} = w_{ij}^{k-1} + \frac{1}{N} \xi_i^k \xi_j^k - \frac{1}{N} \xi_i^k h_{ji}^k - \frac{1}{N} h_{ij}^k \xi_j^k \tag{5}$$

From the above learning rules, it enables the properties of local and incremental for updating the connectivity weight information and increases, if there is no need for information from any other previously trained pattern respectively. Herein (4) and (5), the w_{ij}^k is the weight estimated between i and j only after the k^{th} pattern is learned, ξ^k denotes the new learning pattern and the local field h_{ij}^k is given as:

$$h_{ij}^{k} = \sum_{n=1, n \neq i, j}^{N} w_{in}^{k-1} \xi_n^k \tag{6}$$

Hopfield neural network is designed to classify the loads based on the utilization of categorizes of household appliances. Figure 38 depicts the Hopfield network with a single layer for classifying the load, the inputs from the residencies are $\{x_1, x_2, x_3, \ldots x_i \ldots., x_N\}$ and the corresponding outputs are $\{y_1, y_2, y_3, \ldots y_i \ldots., y_N\}$. The inputs are received from each

SMs that are deployed in the residencies $\{R_1, R_2, R_3, \ldots\ldots, R_N\}$. Output in Hopfield network is obtained for each residency in the determination of their current class.

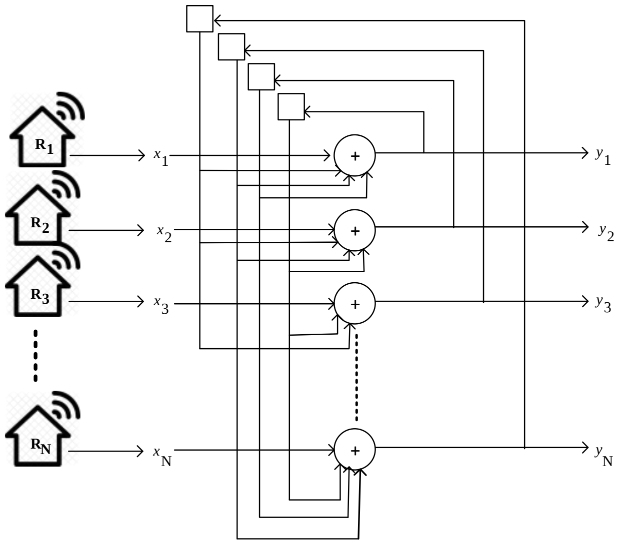

Figure 38 Hopfield network in SRS-LM.

The significance of Hopfield neural network is its use of associative memory. This memory is enabled to store part of the information using which the rest of the pattern is recollected. Recalling the previous patterns supports to have prior knowledge of load class for each residency. The load is categorized into three classes as shown in Table 17.

Table 17 Hopfield neural network based on load classification.

Class	Load type	Condition
1	Active load	All category (I, II and III) appliances are ON
2	Affordable load	Only appliances in category I and II are ON
3	Inactive load	All category (I, II and III) appliances are OFF

The states of nodes in the proposed SRS-LM are estimated as:

$$S = \begin{pmatrix} s_1 & s_2 & \ldots & s_i & \ldots & s_N \end{pmatrix} \tag{7}$$

States s for each node are formulated in a matrix that is trained and here the three classes are the possible states of the load. The state of node s_i is determined as:

$$s_i = sign\left(I_i - Th_N\right) \tag{8}$$

Where Th_N denotes the threshold. Here, $sign\left(x\right) = 1 \forall X \geq 0$ and here, $sign\left(x\right) = -1 \forall X < 0.$ Then the weighted values for each node in the constructed Hopfield network are determined in a matrix i.e. zero diagonal. As in this neural network, no node is connected to itself, it should obey $w = w$ and the weight of the node's connectivity is expressed as:

$$W = \begin{pmatrix} 0 & w_{12} & \cdots & w_{1i} & \cdots & w_{1N} \\ w_{21} & 0 & ,\cdots & w_{2i} & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ w_{i1} & w_{i2} & \cdots & 0 & \cdots & w_{iN} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & w_{Ni} & \cdots & 0 \end{pmatrix} \tag{9}$$

The threshold Th_i is given for each node according to their household appliances that are present. So here it is not necessary to have all the listed household appliances in each residency. Hence the threshold for nodes is given in the matrix format as:

$$Th_N = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_i \\ \vdots \\ \theta_N \end{pmatrix} \tag{10}$$

The terms $\{\theta_1, \theta_2, \ldots\ldots \theta_N\}$ are the individual threshold values for each node. Based on the presence of household appliances in each residency the threshold is varied. If the user includes a new household appliance, then the threshold is also updated. After detecting the load classes of residential sector, the utilization of the categorizing of load at the residency is identified. Then, individual residential payment status is verified and on the other hand, the exact utilization of load by the residency is predicted.

2.3.3.4 Markov chain

Markov chain is used to predict the states of residency based on the pre-defined electricity utilization limit. In this SRS-LM, load prediction, three load states are considered as $X_n = \{s_r, s_c, s_g\}$ i.e. normal state, critical state, and emergency state. Discrete time-based Markov chain which deals with n transition time alternately. The Markov chain process is to determine the load state which can either stay in its previous state or move into another possible state. This Markov chain is also equipped to predict future states with respect to the present state. Let X_0 be the initial state in which the system currently exists.

The transferring probability of the system from one state to another is mathematically represented as:

$$P_{lm} = P_r\left(X_{(n+1)} = m \mid X_n = l\right), \ \forall n = 0,1,2,\ldots \tag{11}$$

Where l and m are the probable states in the system, then the probability of state m after $n+1$ is given as:

$$P_{lm} = P_r(X_{(n+1)} = m \mid X_n = l, X_{(n-1)} = l-1, X_{(n-2)} = l-2 \ldots X_0), \forall n \geq 0, l, m, l-1\ldots \tag{12}$$

The possible state transitions in proposed SRS-LM predict the probability of state transition (see Fig. 39). The transition probability of a system to reach the state of itself is said to be $P_{lm} = 1$. Markov chain for state transition is easier about obtaining successive data.

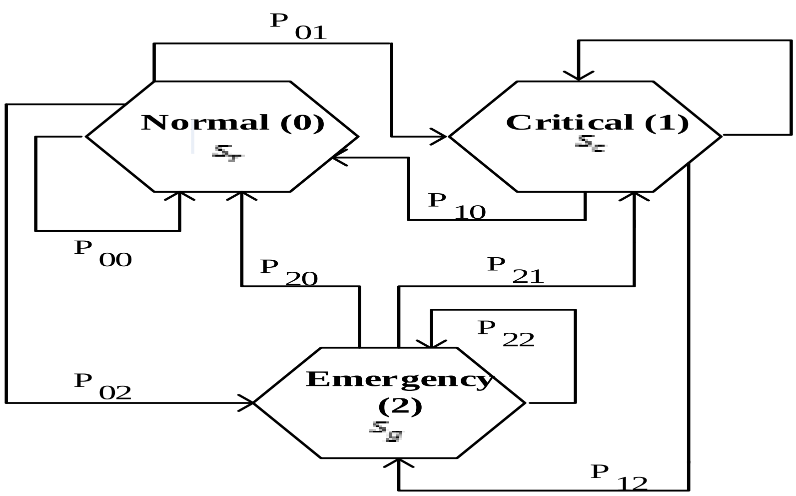

Figure 39 Load status prediction using Markov chain.

Markov chain process predicts a sequence of possible events based on the probability of the events estimated. Each state is possible to change into another state and hence continuous building the Markov chain model. Three states compose the probabilities of state transition for every state. The normal state is $\{P_{00}, P_{01}, P_{02}\}$ where no change of state can happen, move to critical state, or move to emergency state respectively. Similarly, other two states as critical and emergency are supposed to have the probabilities $\{P_{10}, P_{11}, P_{12}\}$ and $\{P_{20}, P_{21}, P_{22}\}$, based on the state transition, the load status of each residency is predicted. If the load status is s_g, then the higher power consuming load in category II and III are insisted to turn it off. In turn, if the load status remains the same as before, then the utility grid is informed to shut down electricity to that residency.

2.3.3.5 Fuzzy logic

In this section, the proposed SRS-LM system is presented to envision and manage load at residential sector along with the provisioning of security for the SM measurements.

Electricity bill payment is one of the essential processes that is involved to detect whether the individual residential owner has paid the bill. Also, we intimate the user to pay bill priory to avoid unnecessary penalties. Fuzzy logic considers last electricity payment date and penalty value for modelling fuzzy rules. Fuzzy logic control system is flexible, and it allows observations from the input parameters. Decision-making problems are efficiently solved, and hence fuzzy logic is used for verifying bill payments.

Table 18 Fuzzy rules.

Inputs		Fuzzy output (F_o)
Previous bill payment (PP)	Penalty (P)	
True	True	Paid
True	False	Paid
False	True	Bill not paid
False	False	Bill not paid

The fuzzy rules are supposed to be binary sets that are comprised of two-valued logic as True / False. Fuzzy logic control system is designed with the functioning of four consecutive blocks as fuzzification, rule base, interference engines, and defuzzification. In SRS-LM, two inputs are considered and processed to retrieve an output whether the payment is completed or incomplete (see Table 18).

- Fuzzy Block I (Fuzzification):

Fuzzification is the first block that receives input parameters and transforms it into operable values of degree of membership functions. Each linguistic term has its degree of membership for the corresponding input parameter. The key processing in fuzzification is mapping the input parameter values involving predefined fuzzy membership functions. Linguistic variables are numerical values that define the scale based on membership functions.

- Fuzzy Block II (Rule Base):

Rule base is the key block present in fuzzy logic system which is deployed with the knowledge of building a set of rules. The rules are developed in 'If-Then' format that mimics operators' logic as AND, OR and NOT. From these Boolean logic operators, OR operator is used in SRS-LM system. The Takagi-Sugeno fuzzy model defines rules as:

Rule 1 – If $(PP = True \mid P_y = True)$, Then $F_o = 1$

Rule 2 – If $(PP = True \mid P_y = False)$, Then $F_o = 1$

Rule 3 – If $(PP = False \mid P_y = True)$, Then $F_o = 0$

Rule 4 – If $(PP = False \mid P_y = False)$, Then $F_o = 0$

The true and false represents 1 and 0 respectively, the output F_O having 1 and 0 denotes bill paid customer and bill unpaid customer. | is the OR operator which is used to define fuzzy rules. The membership functions are modeled into triangular sets having equal widths.

- Fuzzy Block III (Interference Engine):

Interference engine handles three steps as aggregation, activation, and accumulation. The aggregation is performed for estimating the degree of fulfillment (d_{ff}) for the defined f rules. Then activation is involved to mitigate the d_{ff} by determining a weighted factor $w_f \in [0,1]$. Using this, the d_{ff} is altered as follows:

$$d_{ff}^* = w_f * d_{ff} \tag{13}$$

Where d_{ff}^* is defined as a degree of confidence that is determined for adapting the defined rules under the considered input-output relationship. On reducing the d_{ff} for each rule, then accumulation is determined by summing up all the output. As a result, the rules are constructed with two inputs and single output variable.

- Fuzzy Block IV (Defuzzification):

The variables in this block are converted into crisp values for processing. Center of gravity method is presented in defuzzification. Finally, the crisp output F_o is mathematically estimated using center of gravity as:

$$F_O = \frac{\sum_i \mu(c_i) c_i}{\sum_i \mu(c_i)} \tag{14}$$

From this, c_i is the discrete point running and $\mu(c_i)$ is the membership value that is defined in the corresponding membership function.

Fuzzy logic having higher precision and efficiencies for estimating the customer's payment details at a faster rate. A set of four rules as 2^p i.e. $p = 2$ denotes the total number of input parameters, hence $2^2 = 4$. These two parameters are enough to verify the user's payment. If the output is false, then the residential customer will be receiving a warning message to pay the bill via their IoT device. This warning message will include the cost to be paid for the energy consumed from their residential household appliances use. Power consumption cost [131] is determined from the following formulation:

$$C(R_i^t)=\begin{cases} C_1^t \times R_i^t & if \quad R_s^t \le G_s^t \\ C_1^t \times R_i^t & if \quad R_s^t > G_i^t \,\&\, R_i^t \le p_i^t \\ C_1^t \times p_i^t + C_2^t \times (R_i^t - p_i^t)^2 & if \quad R_s^t > G_s^t \,\&\, R_i^t \le p_i^t \end{cases} \tag{15}$$

$C\left(R_i^t\right)$ is the cost of i^{th} residency at time t that is estimated from total power consumption $G_s = G_s^1, G_s^2, \ldots, G_s^T$, where T is the time slot in a day, p_i^t is the power allocated for the particular customer i. The cost per customer is determined and their payment amounts will be included in the message.

2.3.3.6 User security

The proposed SRS-LM offers user security by encrypting electricity readings using hybrid blowfish and ECC algorithms. IoT users are enabled to access their household electricity utilization and keep update with the increase in load. Monitoring of load is associated to minimize electricity cost. In hybrid blowfish and ECC, a random number is generated [132]. Here in this proposed SRS-LM system, the integrated blowfish uses ECC for the generation of that random number. The unique point from ECC is used as a random number.

Blowfish is a symmetric-key cryptography that splits the message into blocks and encrypts 64-bit block. Blowfish algorithm performs subkey generation and encryption/decryption. The key size differs between 32 bits to 448 bits. Here 18, 32-bit sub-keys are composed by using P-arrays. This array initializes 4-s boxes and then P-arrays are XORed for generating sub-keys. Determine a random number from the ECC algorithm. Let the ECC curve equation be:

$$y^2 = x^3 + ax + b \tag{16}$$

Two points P_1 and P_2 are selected from ECC as a new random number which is said to be 64-bit. Combining both P_1 and P_2 convert them into binary form for random number generation. This number should exist with a minimum of five 1’s in its least significant 16-bit. Based on the 1’s position in the least significant bit, the function is operated in 16 rounds. The plain text is performed XOR operation with the generated ransom number and then they are divided into two sub-divisions. The sub-divisions are swapped on each iteration until total iterations are reached. Lastly, the two divisions are recombined, and encryption is terminated.

The encrypted plain text is updated on user side, while accessing the user decrypts and views the original measurement status. Since the increased theft of mobile devices, in the SRS-LM system only a partial key is stored in the device. IF a customer requests to access the information from the SRS-LM system, he/she will be authenticated based on the behavioural information. This information includes typing speed, location, and others. Only after authentication, the partial key will be provided for decryption. In this SRS-LM system, security is ensured even in the case of lost IoT devices. If the device is lost, then the user can register with a new device into the SRS-LM system and receive partial keys to keep updated with the electricity utilization.

2.3.4 Results and Discussion

A simulation environment is constructed using the parameters that are highlighted in Table 19. The simulation parameters are not limited to this. SRS-LM system is proposed with load prediction and security in residential sector. The SRS-LM system model is developed in network simulator–3.26 (Ns-3) installed on Ubuntu 14.04 LTS operating system. The developed SRS-LM is executed using two commands as '*sudo ./waf configure*' and '*sudo ./waf build*'.

This work is implemented in a simulation tool, we have properly specified individual residency with the above-discussed number of household appliances and their appropriate power consumption values are fed into. Table 20 depicts the load and their load values which is used in SRS-LM system.

From the load power of each household appliance, SM in individual residency delivers the values to the server. The server is fed with a three-fold load balancing with hybrid cryptography algorithm. Using the parameters as shown in the above table, the simulation setup is generated as depicted in Fig. 40. According to the simulation setup, the proposed SRS-LM system's results are obtained and compared with previous USEM.

Table 19 Simulation parameters.

Entities	Specifications
Simulation area	1000 x 1000 m
Number of SMs (Static)	25
Number of IoT devices (Dynamic)	25
Load management server	1
Number of measurement packets generated	50 – 100
Measurement time interval	5 – 7 seconds
Mobility model (IoT mobile device)	Random waypoint mobility model
Mobility speed	10 – 50 mps
Transmission rate	100 Mbps
Simulation time	300 seconds

Table 20 Load power consumption.

Category	ID	Load	Power rating / kW
I	01	Light (Fluorescent lamp)	0.04
	02	Fan	0.10
	03	Microwave oven	0.8
	04	Personal computer (charging)	0.05
II	05	Air conditioner	1.5
	06	Air cooler	1.0
	07	Water heater	2.0
	08	Refrigerator	2.4
III	09	Water pumps	2.3
	10	Grinder	0.5
	11	Dishwasher	2.1

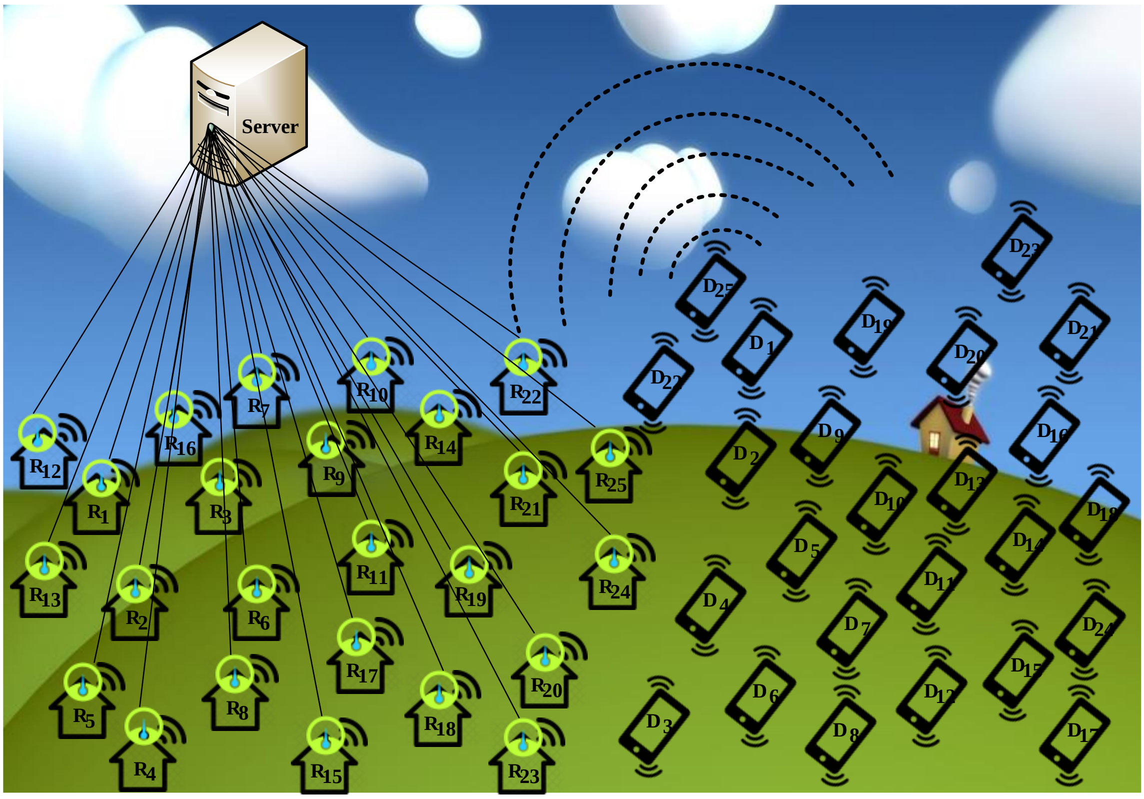

Figure 40 Ns-3 SRS-LM simulation setup.

2.3.4.1 Comparative results

The proposed SRS-LM system procedure is compared with USEM and the performance efficiencies are discussed. In USEM, the load management system emergency load was determined from the user-defined load condition. However, it works well for a single residency it tends to cause improper management among a residential sector. The performance is evaluated in terms of the following metrics as load power, peak load reduction, power cost, power utilization and computational time.

2.3.4.2 Load power

Load power is defined as the power consumed by different household appliances at residency. The load power is variable in accordance with the presence of appliances in residency.

According to increasing in the number of residencies, power increases due to the use of all categories of household appliances. Figure 41 demonstrates the performance of load power by comparing the proposed SRS-LM with USEM. In USEM, a single residency consumes 0 – 80kW, whereas our proposed work SRS-LM deals with 25 residencies and the load power is little higher than the previous work. As per the increase in execution time, the number of residencies operation is increased and hence the load is gradually increased, but the prediction of accurate load status manages load at residential sector with 25 residencies. The variation in minimum to maximum power for each household appliance is involved in load power estimation.

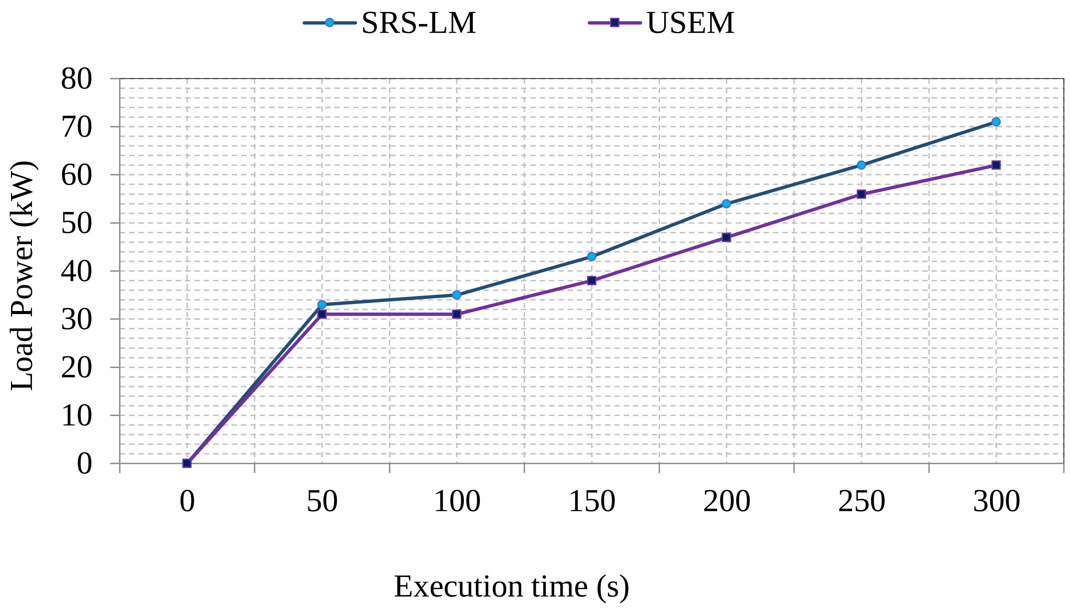

Figure 41 Comparative results for load power.

2.3.4.3 Peak load reduction

Peak load reduction is present to manage the load when it exceeds the limit. The minimization in peak load reflects on reduction in power cost of each consumer. Peak load reduction requires accurate load prediction.

In SRS-LM peak load is predicted from Markov chain which initially identifies the load category in which that residency is activated currently. Figure 42 depicts the comparison of peak load reduction of proposed and existing USEM.

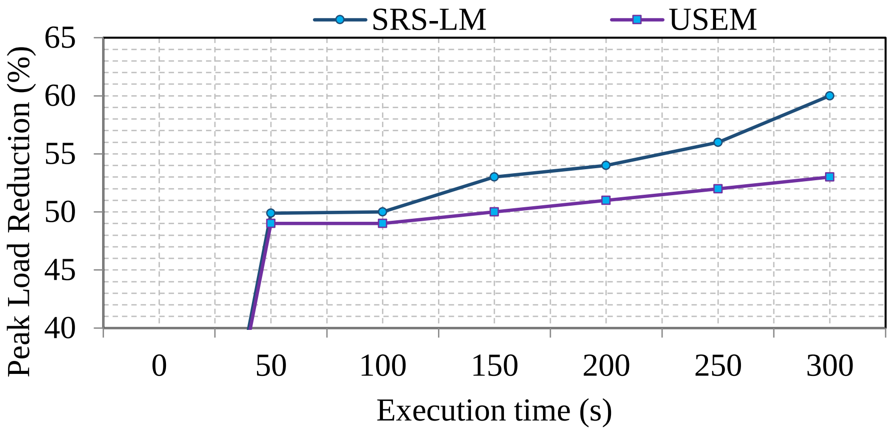

Figure 42 Comparative results for the peak load minimization.

In SRS-LM, nearly 40% of peak load is reduced for increasing number of residencies. On increasing the residencies, the utilization of their appliances is also increased gradually. Comparatively, USEM also reduces up to 35% of load but which was minimized for a residency. The accurate classification of load and then prediction of load achieves higher peak load reduction in SRS-LM. Peak load reduction for 25 residencies greatly impacts on minimizing power cost for all the consumers and dynamic management of emergency load is a potential benefit for consumers.

2.3.4.4 Power cost

Power cost is a significant metric that estimates the price for the utilized electricity power. Increasing electricity usage and ignoring peak load reduction will certainly lead to higher power costs. Power cost is estimated from the above sections using the formulated equation (15). Detecting peak load in SRS-LM and USEM is designed to minimize the power cost of the consumer. Power cost for residency is varied timely based on the use of different household appliances.

Figure 43 shows comparison results of SRS-LM and USEM based on their power cost. When the execution time reaches 300s, all 25 residencies are active state by using certain load whereas in USEM a single residency is present entirely. Power cost is an increasing factor that gradually increases in peak times and it has eventual reduction while managing loads efficiently. Power cost is estimated in terms of kW i.e. electricity use.

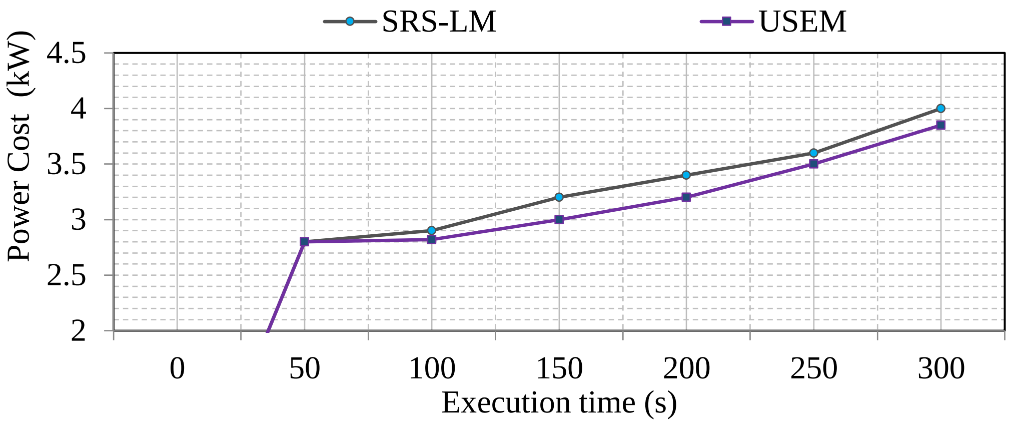

Figure 43 Comparative results for power cost.

2.3.4.5 Power utilization

Power utilization is analysed in terms of power usage and total power consumption in the deployed environment. In Table 21, the power usage with respect to the number of residency and power consumption is given with respect to execution time.

Table 21 Power utilization

Number of residencies	Power usage (kW)		Execution time (s)	Total power consumption (kW)	
	SRS-LM	USEM		SRS-LM	USEM
5	11	12	100	41	42
10	14	15	150	42	43
15	19	21	200	43	45
20	28	30	250	45	48
25	41	45	300	50	52

* Taken from [133].

The existing USEM is presented for more than one residence which resulted in higher utilization of power than the SRS-LM. However, only a smaller variation in power utilization, it impacts the changes in total power consumption. Minimizing the total power consumption by balancing the load is the key goal of SRS-LM. Monitoring SM measurements and predicting the load obtain moderate power consumption.

2.3.4.6 Computational time

Load in individual residency is predicted using three-fold load balancing which deals with certain mathematical computations to identify the load and update customers through their IoT device. Computation time is determined for predicting load status of residency.

Computational time is plotted concerning the number of increasing residencies as depicted in Fig. 44. Computation time gradually increases with the growth of the number of residencies, since additional involvement of residency includes processing of household appliances.

This comparison shows, the computation time for proposed SRS-LM decreases while USEM has higher time to predict load status.

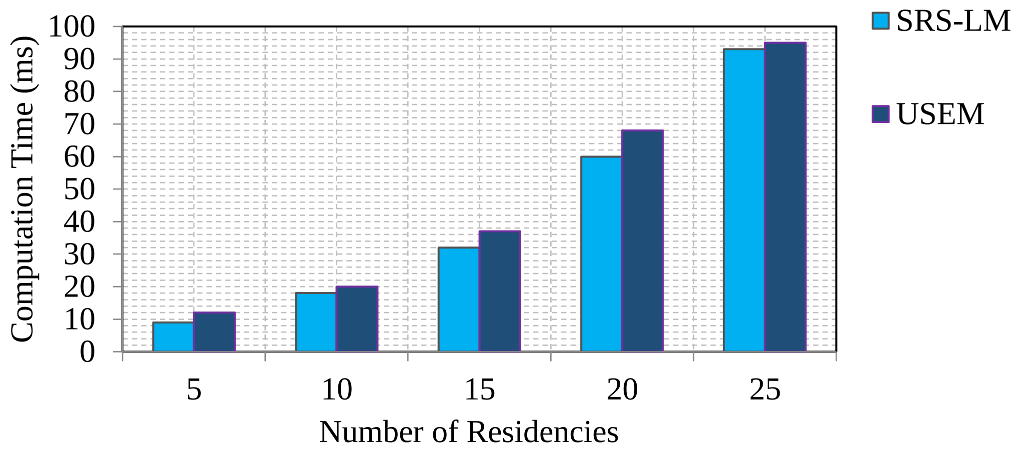

Figure 44 Comparative results for computational time.

The Hopfield neural network and Markov chain in SRS-LM guarantees lesser time for computations to predict load accurately. While in previous USEM the load is predicted based on user-defined threshold values.

The load preference by the owner is not advisable since it creates electricity scarcity problem and different limits by each residency become complex and consume time for load prediction.

2.3.4.7 Security analysis

Security is majorly focused in this paper by presenting a hybrid algorithm that integrates blowfish with ECC algorithm. The measured values from SMs are securely accessed by consumers using their IoT devices. Initially, the originality of SM is verified by generating MAC, later the data are encrypted using a hybrid algorithm and stored.

The stored information is periodically updated according to the changes in power consumption. This information is accessed from anywhere by the user. Table 22 illustrates the execution time of blowfish ECC algorithm, whose data size is 1 KB. Here the SM measurements are numerical values of power readings, and those data are smaller in size. The performance of blowfish ECC algorithm in SRS-LM is evaluated in terms of authentication, confidentiality, and data integrity. The three constraints of security analysis are discussed below.

Table 22 Execution time for hybrid algorithm

Number of rounds	Execution time (s)
4	0.08
8	0.09
12	0.12
16	0.14

* Taken from [133].

2.3.4.8 Authentication

In proposed SRS-LM, the communication is authentic since the behavior of the user is determined. Behavior is based on the details of built-in sensors that are extracted. Here it is not possible for a third person to access SM data since only a partial key is present in IoT device. Also, it gives the SM data only after authenticating user based on their behavior.

2.3.4.9 Confidentiality

This constraint is also attained in SRS-LM system which stores the data after encrypting it. Encrypting the SM measurements and load status information using a hybrid blowfish ECC algorithm enables to provide confidentiality since no one can read this information unless the corresponding user is authenticated and decrypt the information.

2.3.4.10 Integrity

The SM values in SRS-LM are encrypted and so it can be altered by any third party. The communication between IoT and server is handled in a secure channel. Also, the users are authenticated before receiving the information which ensures data integrity.

The proposed SRS-LM system is accomplished with the goal of load management and security. Load management is attained by three-fold process of load category detection, load status prediction, and bill payments verification. On the other hand, security is provisioned by authenticating SM, authenticating IoT device and hybrid cryptography-based secure data access. Also, to minimize computations and memory limitations in IoT device partial key is stored which supports security even if the device is stolen.

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Chapter 3. Discussion, Conclusions, and Future Work

3.1 DISCUSSION AND CONCLUSIONS

This section is divided into two categories: discussion and conclusion of each publication related to every stage described in the first chapter of this thesis, and its future work considered for further development. As previously mentioned, the scope of the first stage was to implement the design of low-cost energy systems for microgrids so the paper "*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*" helped to identify microgrid's energy consumption patterns. Energy-saving opportunities to optimize energy consumption were identified by analysing patterns. The proposed system uses open-source technologies and standards to be user-friendly, scalable, and adaptable. A case study of the implementation of the system in an academic microgrid testbed is presented to demonstrate its effectiveness and practicality. Developing low-cost and accessible SCADA systems for microgrids can significantly affect the adoption and implementation of microgrid technologies, especially in developing countries and remote areas. The proposed system can also be valuable for education and outreach activities to promote awareness and understanding of microgrid technologies and applications. A low-cost monitoring system can provide valuable information about energy consumption and help identify areas for energy efficiency improvements, leading to reduced energy costs and increased energy efficiency. Furthermore, identifying and analysing energy consumption patterns is crucial in developing effective energy management strategies. Low-cost monitoring systems can provide valuable insights into energy usage, reducing energy costs and increasing energy efficiency.

The second stage contemplated bioinspired algorithms to support energy efficiency in microgrids. Thus, the paper "A Cascade Hybrid PSO Feed-Forward Neural Network Model of a Biomass Gasification Plant for Covering the Energy Demand in an AC Microgrid" proposes a hybrid model that combines particle swarm optimization (PSO) and a feed-forward neural network (FFNN) to model the energy production of a biomass gasification plant and to cover the energy demand in an AC microgrid. The proposed model consists of two steps. In the first step, PSO is used to optimize the FFNN architecture and to train the network on a dataset of historical energy production and consumption data. The PSO algorithm adjusts the weights and biases of the FFNN to minimize the error between the predicted and actual energy production and consumption. In the second one, the FFNN trained is used to predict the biomass gasification plant's energy production and optimize the microgrid's operation. The FFNN model is used in cascade with a proportional-integral-derivative (PID) controller, which adjusts the gasification plant's setpoint to match the microgrid's predicted energy demand. The proposed model is validated using a case study of a real biomass gasification plant connected to an AC microgrid. The results showed that the hybrid PSO-FFNN model can accurately predict the gasification plant's energy production and optimize the microgrid's operation, leading to improved energy efficiency and reduced energy costs. It was demonstrated that the potential of combining PSO and FFNN in a hybrid model to model the energy production of a biomass gasification plant can optimize the operation of an AC microgrid. The proposed model can effectively support energy management in microgrids with distributed energy resources, leading to improved energy efficiency and reduced energy costs.

Discussing ANN models, it is possible to use them to predict energy demand with high accuracy once trained. By accurately predicting energy demand, it is possible to optimize energy supply and ensure that energy systems are running efficiently. They can also optimize energy generation by predicting energy demand and adjusting the generation accordingly. This can help to minimize waste and reduce the cost of energy production. Besides, they can be used to integrate renewable energy sources, such as solar and wind power, into the energy system. By predicting energy demand and adjusting the generation, accordingly, optimizing the use of renewable energy sources and reducing reliance on non-renewable sources is possible.

ANN models help monitor energy consumption in real time, providing information about energy usage and identifying potential issues with energy systems. This can help optimize energy consumption and ensure energy systems work efficiently. Finally, they can be used to predict energy storage requirements based on energy demand and generation. By predicting energy storage requirements, optimizing the use of energy storage systems, and ensuring that energy systems are running efficiently is possible. In summary, ANN models can provide valuable information about energy demand and supply, reducing energy costs and increasing energy efficiency.

In the third and final stage, the integration of ML techniques in LMS was considered. An SRS-LM system was proposed and tested for load management in the residential sector with the provisioning of secure access by customers using IoT devices. The readings from SMs are authenticated with MAC, and then based on the measurements, they are categorized into different loads. Three-fold lad management is presented by designing a Hopfield neural network, Markov chain, and fuzzy logic. Hopfield neural network classifies the load into three categories: active, affordable, and inactive. Furthermore, the Markov chain predicts the current load status as normal, critical, or emergency. This load status is enabled to give a warning message to turn off excessively used load at residency. SRS-LM ensures secure accessing of SM measurements and load status by the applied hybrid cryptography algorithm. The Blowfish algorithm is integrated with the ECC algorithm. The Blowfish procedure is followed in which ECC undergoes the random number generation. The comparative results for power utilization, peak load reduction, power cost and computation time have proven its efficiency better than the previous USEM system. In the future, we have planned to concentrate on a demand-side load management system. Using machine learning techniques in a Load Management System model can provide valuable insights into energy consumption patterns, leading to reduced energy costs, increased energy efficiency, and a more sustainable energy system.

3.2 FUTURE WORK

This thesis considered some aspects of an optimized model for energy management systems and load control, some potential lines of research for the first publication, “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” are:

- Focusing on data integration from multiple sources, including weather data, occupancy data, peak-hours usage, high-demand appliance, and building/home automation systems, to gain a more comprehensive understanding of energy consumption patterns integrating new technologies and infrastructure and considering energy policies.

- Developing more advanced data analytics techniques with the use of machine learning techniques that can provide valuable insights into energy consumption patterns. Future work could focus on developing more advanced data analytics techniques, such as deep learning and reinforcement learning, to improve the accuracy and reliability of energy consumption predictions.

- Improving energy management strategies to focus on developing more advanced energy management strategies that incorporate real-time energy consumption data. These strategies could be used to optimize energy usage, reduce energy costs, and improve energy efficiency considering real-time pricing according to the current network tariffs and the impact on consumers and prosumers.

Related to ANN models for covering energy demand, future work for the second publication "A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid" can include:

- Optimizing hyperparameters for a better performance of many ANN models. Developing more efficient methods for selecting these hyperparameters, such as the learning rate, batch size, and number of hidden layers.

- Developing more advanced ANN architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Exploring the use of these advanced architectures for energy demand forecasting may lead to more accurate and reliable predictions.

For the last publication "A smart residential security assisted load management system using hybrid cryptography", potential areas for future work on machine learning techniques in load management system models could include:

- Designing and developing more advanced machine learning algorithms such as deep learning and reinforcement learning for more efficient and effective load management strategies. Likewise, a system that can learn and adapt to any changing conditions in real time should be important to consider so developing adaptive strategies that can respond to changes in energy demand or supply could be explored.

- This technology can be used to predict demand and optimize distributed systems in real-time; therefore a future work is to integrate the technology into a real application integrating electricity generation by renewable sources and doing tests with an off-grid microgrid (standalone applications) and on-grid MG.

3.3 DISCUSIÓN Y CONCLUSIONES

Esta sección se divide en dos categorías: discusión y conclusión de cada publicación relacionada con cada una de las etapas descritas en el primer capítulo de esta tesis, y su trabajo futuro considerado para su posterior desarrollo. Como se mencionó anteriormente, el alcance de la primera etapa fue implementar el diseño de sistemas de energía de bajo costo para microrredes, por lo que el artículo "Sistema de control de supervisión y adquisición de datos basado en la web de bajo costo para un banco de pruebas de microrredes: un estudio de caso en diseño e implementación para aplicaciones académicas y de investigación" ayudó a identificar los patrones de consumo de energía de las microrredes. Se identificaron oportunidades de ahorro de energía para optimizar el consumo de energía mediante el análisis de patrones. El sistema propuesto utiliza tecnologías y estándares de código abierto para ser fácil de usar, escalable y adaptable. Se presenta un estudio de caso de la implementación del sistema en un banco de pruebas de microrredes académicas para demostrar su efectividad y practicidad. El desarrollo de sistemas SCADA accesibles y de bajo costo para microrredes puede afectar significativamente la adopción e implementación de tecnologías de microrredes, especialmente en países en desarrollo y áreas remotas. El sistema propuesto también puede ser valioso para las actividades de educación y divulgación para promover el conocimiento y la comprensión de las tecnologías y aplicaciones de las microrredes. Un sistema de monitoreo de bajo costo puede proporcionar información valiosa sobre el consumo de energía y ayudar a identificar áreas para mejoras de eficiencia energética, lo que lleva a una reducción de los costos de energía y una mayor eficiencia energética. Además, la identificación y el análisis de los patrones de consumo de energía son cruciales para desarrollar estrategias eficaces de gestión de la energía. Los sistemas de monitoreo de bajo costo pueden proporcionar información valiosa sobre el uso de energía, reduciendo los costos de energía y aumentando la eficiencia energética.

La segunda etapa contempló algoritmos bio-inspirados para apoyar la eficiencia energética en microrredes. Así, el artículo "A Cascade Hybrid PSO Feed-Forward Neural Network Model of a Biomass Gasification Plant for Covering the Energy Demand in an AC Microgrid" propone un modelo híbrido que combina la optimización del enjambre de partículas (PSO) y una red neuronal feed-forward (FFNN) para modelar la producción de energía de una planta de gasificación de biomasa y cubrir la demanda de energía en una microrred de CA. El modelo propuesto consta de dos pasos. En el primer paso, PSO se utiliza para optimizar la arquitectura FFNN y entrenar la red con un conjunto de datos históricos de producción y consumo de energía. El algoritmo PSO ajusta los pesos y sesgos del FFNN para minimizar el error entre la producción y el consumo de energía previstos y reales. En el segundo, el FFNN entrenado se utiliza para predecir la producción de energía de la planta de gasificación de biomasa y optimizar la operación de la microrred. El modelo FFNN se utiliza en cascada con un controlador proporcional-integral-derivativo (PID), que ajusta el punto de ajuste de la planta de gasificación para que coincida con la demanda de energía prevista de la microrred. El modelo propuesto se valida mediante un estudio de caso de una planta de gasificación de biomasa real conectada a una microrred de corriente alterna. Los resultados mostraron que el modelo híbrido PSO-FFNN puede predecir con precisión la producción de energía de la planta de gasificación y optimizar el funcionamiento de la microrred, lo que conduce a una mayor eficiencia energética y a una reducción de los costes energéticos. Se demostró que el potencial de combinar PSO y FFNN en un modelo híbrido para modelar la producción de energía de una planta de gasificación de biomasa puede optimizar el funcionamiento de una microrred de CA. El modelo propuesto puede apoyar eficazmente la gestión de la energía en microrredes con recursos energéticos distribuidos, lo que conduce a una mejora de la eficiencia energética y a una reducción de los costes energéticos.

Hablando de los modelos de ANN, es posible utilizarlos para predecir la demanda de energía con alta precisión una vez entrenados. Al predecir con precisión la demanda de energía, es posible optimizar el suministro de energía y garantizar que los sistemas de energía funcionen de manera eficiente. También pueden optimizar la generación de energía mediante la predicción de la demanda de energía y el ajuste de la generación en consecuencia. Esto puede ayudar a minimizar el desperdicio y reducir el costo de producción de energía. Además, se pueden utilizar para integrar fuentes de energía renovables, como la solar y la eólica, en el sistema energético. Al predecir la demanda de energía y ajustar la generación en consecuencia, es posible optimizar el uso de fuentes de energía renovables y reducir la dependencia de fuentes no renovables.

Los modelos ANN ayudan a monitorear el consumo de energía en tiempo real, proporcionando información sobre el uso de energía e identificando posibles problemas con los sistemas de energía. Esto puede ayudar a optimizar el consumo de energía y garantizar que los sistemas de energía funcionen de manera eficiente. Por último, se pueden utilizar para predecir las necesidades de almacenamiento de energía en función de la demanda y la generación de energía. Es posible predecir los requisitos de almacenamiento de energía, optimizar el uso de los sistemas de almacenamiento de energía y garantizar que los sistemas de energía funcionen de manera eficiente. En resumen, los modelos de RNA pueden proporcionar información valiosa sobre la demanda y el suministro de energía, reduciendo los costes energéticos y aumentando la eficiencia energética.

En la tercera y última etapa, se consideró la integración de técnicas de ML en LMS. Se propuso y probó un sistema SRS-LM para la gestión de la carga en el sector residencial con el aprovisionamiento de un acceso seguro por parte de los clientes que utilizan dispositivos IoT. Las lecturas de los SM se autentican con MAC y, a continuación, en función de las mediciones, se clasifican en diferentes cargas. La gestión de tres grupos se presenta mediante el diseño de una red neuronal de Hopfield, una cadena de Markov y una lógica difusa. La red neuronal de Hopfield clasifica la carga en tres categorías: activa, asequible e inactiva. Además, la cadena de Markov predice el estado actual de la carga como normal, crítico o de emergencia. Este estado de carga está habilitado para dar un mensaje de advertencia para desactivar la carga excesivamente utilizada en la residencia. SRS-LM garantiza el acceso seguro a las mediciones de SM y al estado de carga mediante el algoritmo de criptografía híbrida aplicado. El algoritmo Blowfish está integrado con el algoritmo ECC. Se sigue el procedimiento Blowfish en el que ECC se somete a la generación de números aleatorios. Los resultados comparativos para la utilización de la energía, la reducción de la carga máxima, el costo de la energía y el tiempo de cálculo han demostrado su eficiencia mejor que el sistema USEM anterior. En el futuro, hemos planeado concentrarnos en un sistema de gestión de carga del lado de la demanda. El uso de técnicas de aprendizaje automático en un modelo de sistema de gestión de carga puede proporcionar información valiosa sobre los patrones de consumo de energía, lo que conduce a una reducción de los costos de energía, una mayor eficiencia energética y un sistema energético más sostenible.

3.4 TRABAJO FUTURO

En esta tesis se consideraron ciertos elementos en un modelo optimizado para sistemas de gestión energética y control de carga, algunas líneas potenciales de investigación para la primera publicación "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" son:

- Centrarse en la integración de datos de múltiples fuentes, incluidos datos meteorológicos, datos de ocupación, uso de horas pico, electrodomésticos de alta demanda y sistemas de automatización de edificios / hogares, para obtener una comprensión más completa de los patrones de consumo de energía integrando nuevas tecnologías e infraestructura y considerando políticas energéticas.

- Desarrollar una técnica de análisis de datos más avanzada con el uso de técnicas de aprendizaje automático que pueden proporcionar información valiosa sobre los patrones de consumo de energía. El trabajo futuro podría centrarse en el desarrollo de técnicas de análisis de datos más avanzadas, como el aprendizaje profundo y el aprendizaje por refuerzo, para mejorar la precisión y la fiabilidad de las predicciones de consumo de energía.

- Mejorar las estrategias de gestión energética para centrarse en el desarrollo de estrategias de gestión de la energía más avanzadas que incorporen datos de consumo de energía en tiempo real. Estas estrategias podrían utilizarse para optimizar el uso de energía, reducir los costos de energía y mejorar la eficiencia energética teniendo en cuenta los precios en tiempo real de acuerdo con las tarifas de red actuales y el impacto en los consumidores y prosumidores.

En relación con los modelos ANN para cubrir la demanda de energía, el trabajo futuro para la segunda publicación "A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid" puede incluir:

- Optimización de hiperparámetros para un mejor rendimiento de muchos modelos ANN. Desarrollar métodos más eficientes para seleccionar estos hiperparámetros, como la tasa de aprendizaje, el tamaño del lote y el número de capas ocultas.

- Desarrollar arquitecturas ANN más avanzadas, como redes neuronales convolucionales (CNN) y redes neuronales recurrentes (RNN). Explorar el uso de estas arquitecturas avanzadas para la previsión de la demanda de energía puede conducir a predicciones más precisas y fiables.

Para la última publicación "Un sistema inteligente de gestión de carga asistido por seguridad residencial utilizando criptografía híbrida", las áreas potenciales para el trabajo futuro sobre técnicas de aprendizaje automático en modelos de sistemas de gestión de carga podrían incluir:

- Diseñar y desarrollar algoritmos de aprendizaje automático más avanzados, como el aprendizaje profundo y el aprendizaje por refuerzo, para estrategias de gestión de carga más eficientes y efectivas. Del mismo modo, debería ser importante considerar un sistema que pueda aprender y adaptarse a cualquier condición cambiante en tiempo real, por lo que se podría explorar el desarrollo de estrategias adaptativas que puedan responder a los cambios en la demanda o el suministro de energía.

- Esta tecnología se puede utilizar para predecir la demanda y optimizar los sistemas distribuidos en tiempo real; por lo tanto, un trabajo futuro es integrar la tecnología en una aplicación real, integrando la generación de electricidad mediante fuentes renovables y haciendo pruebas con una microrred aislada (aplicaciones independientes) y MG en red.

3.5 DISCUSSIÓ Y CONCLUSIONS

Esta secció es divideix en dues categories: discussió i conclusió de cada publicació relacionada amb cadascuna de les etapes descrites en el primer capítol d'esta tesi, i el seu treball futur considerat per al seu posterior desenvolupament. Com es va esmentar anteriorment, l'abast de la primera etapa va ser implementar el disseny de sistemes d'energia de baix cost per a microxarxes, per la qual cosa l'article "Sistema de control de supervisió i adquisició de dades basat en la web de baix cost per a un banc de proves de microxarxes: un estudi de cas en disseny i implementació per a aplicacions acadèmiques i d'investigació" va ajudar a identificar els patrons de consum d'energia de les microxarxes. Es van identificar oportunitats d'estalvi d'energia per a optimitzar el consum d'energia mitjançant l'anàlisi de patrons. El sistema proposat utilitza tecnologies i estàndards de codi obert per a ser fàcil d'usar, escalable i adaptable. Es presenta un estudi de cas de la implementació del sistema en un banc de proves de microxarxes acadèmiques per a demostrar la seua efectivitat i practicitat. El desenvolupament de sistemas SCADA accessibles i de baix cost per a microxarxes pot afectar significativament l'adopció i implementació de tecnologies de microxarxes, especialment en països en desenvolupament i àrees remotes. El sistema proposat també pot ser valuós per a les activitats d'educació i divulgació per a promoure el coneixement i la comprensió de les tecnologies i aplicacions de les microxarxes. Un sistema de monitoratge de baix cost pot proporcionar informació valuosa sobre el consum d'energia i ajudar a identificar àrees per a millores d'eficiència energètica, la qual cosa porta a una reducció dels costos d'energia i una major eficiència energètica. A més, la identificació i l'anàlisi dels patrons de consum d'energia són crucials per a desenvolupar estratègies eficaces de gestió de l'energia. Els sistemes de monitoratge de baix cost poden proporcionar informació valuosa sobre l'ús d'energia, reduint els costos d'energia i augmentant l'eficiència energètica.

La segona etapa va contemplar algorismes bio-inspirats per a donar suport a l'eficiència energètica en microxarxes. Així, l'article "A Cascade Hybrid PSO Feed-Forward Neural Network Model of a Biomass Gasification Plant for Covering the Energy Demand in an AC Microgrid" proposa un model híbrid que combina l'optimització de l'eixam de partícules (PSO) i una xarxa neuronal feed-forward (FFNN) per a modelar la producció d'energia d'una planta de gasificació de biomassa i cobrir la demanda d'energia en una microxarxa de CA. El model proposat consta de dos passos. En el primer pas, PSO s'utilitza per a optimitzar l'arquitectura FFNN i entrenar la xarxa amb un conjunt de dades històriques de producció i consum d'energia. L'algorisme PSO ajusta els pesos i biaixos del FFNN per a minimitzar l'error entre la producció i el consum d'energia previstos i reals. En el segon, el FFNN entrenat s'utilitza per a predir la producció d'energia de la planta de gasificació de biomassa i optimitzar l'operació de la microxarxa. El model FFNN s'utilitza en cascada amb un controlador proporcional-integral-derivatiu (PID), que ajusta el punt d'ajust de la planta de gasificació perquè coincidisca amb la demanda d'energia prevista de la microxarxa. El model proposat es valguda mitjançant un estudi de cas d'una planta de gasificació de biomassa real connectada a una microxarxa de corrent altern. Els resultats van mostrar que el model híbrid PSO-FFNN pot predir amb precisió la producció d'energia de la planta de gasificació i optimitzar el funcionament de la microxarxa, la qual cosa condueix a una major eficiència energètica i a una reducció dels costos energètics. Es va demostrar que el potencial de combinar PSO i FFNN en un model híbrid per a modelar la producció d'energia d'una planta de gasificació de biomassa pot optimitzar el funcionament d'una microxarxa de CA. El model proposat pot secundar eficaçment la gestió de l'energia en microxarxes amb recursos energètics distribuïts, la qual cosa condueix a una millora de l'eficiència energètica i a una reducció dels costos energètics.

Parlant dels models d'ANN, és possible utilitzar-los per a predir la demanda d'energia amb alta precisió una vegada entrenats. En predir amb precisió la demanda d'energia, és possible optimitzar el subministrament d'energia i garantir que els sistemes d'energia funcionen de manera eficient. També poden optimitzar la generació d'energia mitjançant la predicció de la demanda d'energia i l'ajust de la generació en conseqüència. Això pot ajudar a minimitzar el desaprofitament i reduir el cost de producció d'energia. A més, es poden utilitzar per a integrar fonts d'energia renovables, com la solar i l'eòlica, en el sistema energètic. En predir la demanda d'energia i ajustar la generació en conseqüència, és possible optimitzar l'ús de fonts d'energia renovables i reduir la dependència de fonts no renovables.

Els models ANN ajuden a monitorar el consum d'energia en temps real, proporcionant informació sobre l'ús d'energia i identificant possibles problemes amb els sistemes d'energia. Això pot ajudar a optimitzar el consum d'energia i garantir que els sistemes d'energia funcionen de manera eficient. Finalment, es poden utilitzar per a predir les necessitats d'emmagatzematge d'energia en funció de la demanda i la generació d'energia. És possible predir els requisits d'emmagatzematge d'energia, optimitzar l'ús dels sistemes d'emmagatzematge d'energia i garantir que els sistemes d'energia funcionen de manera eficient. En resum, els models d'RNA poden proporcionar informació valuosa sobre la demanda i el subministrament d'energia, reduint els costos energètics i augmentant l'eficiència energètica.

En la tercera i última etapa, es va considerar la integració de tècniques de ML en LMS. Es va proposar i va provar un sistema SRS-LM per a la gestió de la càrrega en el sector residencial amb l'aprovisionament d'un accés segur per part dels clients que utilitzen dispositius IoT. Les lectures dels SM s'autentiquen amb MAC i, a continuació, en funció dels mesuraments, es classifiquen en diferents càrregues. La gestió de tres grups es presenta mitjançant el disseny d'una xarxa neuronal de Hopfield, una cadena de Màrkov i una lògica difusa. La xarxa neuronal de Hopfield classifica la càrrega en tres categories: activa, assequible i inactiva. A més, la cadena de Màrkov prediu l'estat actual de la càrrega com a normal, crític o d'emergència. Este estat de càrrega està habilitat per a donar un missatge d'advertiment per a desactivar la càrrega excessivament utilitzada en la residència. SRS-LM garanteix l'accés segur als mesuraments d'SM i a l'estat de càrrega mitjançant l'algorisme de criptografia híbrida aplicat. L'algorisme Blowfish està integrat amb l'algorisme ECC. Se segueix el procediment Blowfish en el qual ECC se sotmet a la generació de números aleatoris. Els resultats comparatius per a la utilització de l'energia, la reducció de la càrrega màxima, el cost de l'energia i el temps de càlcul han demostrat la seua eficiència millor que el sistema USEM anterior. En el futur, hem planejat concentrar-nos en un sistema de gestió de càrrega del costat de la demanda. L'ús de tècniques d'aprenentatge automàtic en un model de sistema de gestió de càrrega pot proporcionar informació valuosa sobre els patrons de consum d'energia, la qual cosa condueix a una reducció dels costos d'energia, una major eficiència energètica i un sistema energètic més sostenible.

3.6 TREBALL FUTUR

En aquesta tesi es van considerar uns certs elements en un model optimitzat per a sistemes de gestió energètica i control de càrrega, algunes línies potencials d'investigació per a la primera publicació "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" són:

- Centrar-se en la integració de dades de múltiples fonts, incloses dades meteorològiques, dades d'ocupació, ús d'hores pique, electrodomèstics d'alta demanda i sistemes d'automatització d'edificis / llars, per a obtindre una comprensió més completa dels patrons de consum d'energia integrant noves tecnologies i infraestructura i considerant polítiques energètiques.

- Desenvolupar una tècnica d'anàlisi de dades més avançada amb l'ús de tècniques d'aprenentatge automàtic que poden proporcionar informació valuosa sobre els patrons de consum d'energia. El treball futur podria centrar-se en el desenvolupament de tècniques d'anàlisis de dades més avançades, com l'aprenentatge profund i l'aprenentatge per reforç, per a millorar la precisió i la fiabilitat de les prediccions de consum d'energia.

- Millorar les estratègies de gestió energètica per a centrar-se en el desenvolupament d'estratègies de gestió de l'energia més avançades que incorporen dades de consum d'energia en temps real. Aquestes estratègies podrien utilitzar-se per a optimitzar l'ús d'energia, reduir els costos d'energia i millorar l'eficiència energètica tenint en compte els preus en temps real d'acord amb les tarifes de xarxa actuals i l'impacte en els consumidors i prosumidors.

En relació amb els models ANN per a cobrir la demanda d'energia, el treball futur per a la segona publicació "A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid" pot incloure:

- Optimització de hiperparámetres per a un millor rendiment de molts models ANN. Desenvolupar mètodes més eficients per a seleccionar aquests hiperparámetres, com la taxa d'aprenentatge, la grandària del lot i el nombre de capes ocultes.

- Desenvolupar arquitectures ANN més avançades, com a xarxes neuronals convolucionals (CNN) i xarxes neuronals recurrents (RNN). Explorar l'ús d'aquestes arquitectures avançades per a la previsió de la demanda d'energia pot conduir a prediccions més precises i fiables.

Per a l'última publicació "Un sistema intel·ligent de gestió de càrrega assistit per seguretat residencial utilitzant criptografia híbrida", les àrees potencials per al treball futur sobre tècniques d'aprenentatge automàtic en models de sistemes de gestió de càrrega podrien incloure:

- Dissenyar i desenvolupar algorismes d'aprenentatge automàtic més avançats, com l'aprenentatge profund i l'aprenentatge per reforç, per a estratègies de gestió de càrrega més eficients i efectives. De la mateixa manera, hauria de ser important considerar un sistema que puga aprendre i adaptar-se a qualsevol condició canviant en temps real, per la qual cosa es podria explorar el desenvolupament d'estratègies adaptatives que puguen respondre als canvis en la demanda o el subministrament d'energia.

- Esta tecnologia es pot utilitzar per a predir la demanda i optimitzar els sistemes distribuïts en temps real; per tant, un treball futur és integrar la tecnologia en una aplicació real, integrant la generació d'electricitat mitjançant fonts renovables i fent proves amb una microxarxa aïllada (aplicacions independents) i MG en xarxa.

Chapter 4. More Publications and Research Activities

This chapter shows all the academic and scientific activities throughout the thesis' research period with highly important contributions over it. The following publications are indexed into the JCR but were not included in the compendium.

4.1 ANOTHER PEER REVIEW PUBLICATIONS

- 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, Elsevier (**JCR, Q1**), 118700. https://doi.org/10.1016/j.eswa.2022.118700

Contributions: selection of the best MPPT optimization model, power converter model design and implementation using Gray Wolf Optimizer, algorithms integration (bio-inspired and traditional algorithms).

- 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, Elsevier **(JCR Q1)**, 267, 115920. https://doi.org/10.1016/j.enconman.2022.115920

Contributions: design and implementation of artificial neural network models, machine learning algorithms integration, simulation evaluation using historical data to get the best ANN results.

- 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 **(JCR Q3),** vol. 6, no. 1, pp. 619-625 (2021). http://dx.doi.org/10.25046/aj060167

Contributions: Three bio-inspired algorithms were tested and validated against traditional PID techniques, simulation results showed better performance with the GWO algorithm than PSO or GA.

- 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 **(JCR Q2)**, 30(11). https://doi.org/10.1002/2050-7038.12617

Contributions: Novel Energy Management Model considering multi-Microgrid design, integration of optimization algorithms with fuzzy logic and game theory with simulations and evaluations.

4.2 RESEARCH STAYS

- Universidad de Guadalajara, Centro Universitario de Tonala. Tonala, Jalisco. Mexico. From 01/18/2022 to 12/17/2022.

4.3 AWARDS AND DISTINCTIONS

- Award for the best presentation on November 13, 2020 at the 8th International Conference on Innovation, Documentation and Teaching Technologies (INNODOCT), Valencia, Spain, for the work "Arduino Based Smart Power Meter: A Low-cost Approach for Academic and Research Applications".

4.4 CONFERENCES

4.4.1 International Conferences

- Chiñas-Palacios, C. D., Vargas-Salgado, C., Aguila-Leon, J., & Hurtado-Perez, E. (2020). Arduino Based Smart Power Meter: A Low-cost Approach for Academic and Research Applications. *8th International Conference on Innovation, Documentation and Education INNODOCT. http://dx.doi.org/10.4995/INN2020.2020.11904*
- C. Vargas Salgado, J. Águila-León, C. Chiñas-Palacios, and D. Alfonso-Solar (2020). Supervisory Control And Data Acquisition system applied to a

researching purpose microgrid based on Renewable Energy. *8th International Conference on Innovation, Documentation and Education INNODOCT.* *http://dx.doi.org/10.4995/INN2020.2020.11898*

- J. Águila-León, C. Vargas Salgado, C. D. Chiñas-Palacios, and E. Hurtado-Pérez. Design and Deployment of a Web SCADA for an Experimental Microgrid. *8th International Conference on Innovation, Documentation and Education INNODOCT/20*. http://dx.doi.org/10.4995/INN2020.2020.11878

- Chiñas-Palacios, C., Aguila-Leon, J., Vargas-Salgado, C., Sotelo-Castañón, J., Hurtado, E. J., & García, E. X. M. (2020). Reducción del Voltaje de Rizado en un Convertidor Elevador DC-DC mediante la Optimización por Enjambre de Partículas. *E-Gnosis*, 18(12), 1–8. http://www.e-gnosis.udg.mx/index.php/e-gnosis/article/view/798/418

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- Vargas-Salgado, C., Chiñas-Palacios, C., Aguila-León, J., & Alfonso-Solar, D. (2019). Measurement of the black globe temperature to estimate the MRT and WBGT indices using a smaller diameter globe than a standardized one:

Experimental analysis. *Proceedings 5th CARPE Conference: Horizon Europe and Beyond*, 201–207. https://doi.org/10.4995/carpe2019.2019.10203

4.4.2 Academic Conferences

- Jesus Aguila-León, Cristian Chiñas-Palacios, Carlos Vargas-Salgado, Elías Hurtado-Pérez, y Francisco Martínez (2020). Competencias para la Responsabilidad Social Universitaria: una Comparativa de Perspectivas entre Universidades. *INRED-2020: VI Congreso de Innovación Educativa y Docencia En Red*.
- Chiñas-Palacios, C. D., Aguila-León, J., Vargas-Salgado, C., Alcázar-Ortega, M., (2019). Questionnaire design in gamification process for education: a case study at Universidad de Guadalajara-Mexico. *International Conference on Innovation, Documentation and Education INNODOCT/19*. https://doi.org/10.4995/INN2019.2019.10123
- L. Montuori; M. Alcázar-Ortega; C. Vargas-Salgado; C. D. Chiñas-Palacios (2019). Development of an interactive tool based on Education ERPs Software to support the learning of Transversal Competences. *International Conference on Innovation, Documentation and Education INNODOCT/19*. https://doi.org/10.4995/INN2019.2019.10090
- D. Ribó-Pérez; P. Bastida-Molina; C. Vargas-Salgado; C. D. Chiñas-Palacios (2019). Introducing a gender perspective in engineering degrees, a case of study in an Energy Markets course. *International Conference on Innovation, Documentation and Education INNODOCT/19*. https://doi.org/10.4995/INN2019.2019.10092
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Chapter 5.
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