Technological Forecasting & Social Change 173 (2021) 121115

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Multi-objective optimization of costs and energy efficiency associated with autonomous industrial processes for sustainable growth

Francisco Rubio *, Carlos Llopis-Albert, Francisco Valero

Instituto Universitario de Ingeniería Mecánica y Biomecánica (I2MB), Universitat Politècnica de València, Camino de Vera s/n, 46022, Valencia, Spain

A R T I C L E I N F O

Keywords:
Sustainable growth
Multi-objective optimization
Pareto frontiers
Production improvement
Energy efficiency
Climate change

A B S T R A C T

Digital technologies are transforming the industrial landscape and disrupting traditional business models. New business opportunities related to Industry 4.0 are emerging, so companies must adapt to the new environment. This work puts forward a multi-objective optimization algorithm to improve productivity and reduce the costs and energy consumption of autonomous industrial processes with the aim of achieving sustainable growth. The processes analyzed encompass an assembly line production with robotic cells and the subsequent material handling systems (MHS) using autonomous guided vehicles (AGVs) for indoor transport. An efficient algorithm has been implemented to integrate and minimize industrial robot arm working times, AGVs travel times and their trajectory, and the energy consumed in industrial processes while maximizing global business profits when manufacturing different products in an indoor industrial environment. Furthermore, this is carried out by considering the kinematics and dynamics of autonomous industrial processes and sustainable strategies to ensure compliance with government policies on environmental issues. These objectives are in line with the European Union (EU) guidelines on reducing greenhouse gas (GHG) emissions, renewable energy share, and improvements in energy efficiency for climate change mitigation and adaptation policies. Based on the difference in energy consumption between optimized and unoptimized industrial processes, the economic benefits can be quantified in terms of GHG emission quotas, volume of fuel consumed, and the indirect benefits with respect to improving corporate brand image. The methodology presented here has been successfully applied to several real case studies covering different manufacturing processes, robotic operations, and products. The results show that higher profits and sustainable growth are achieved when this methodology is used. It helps design Flexible Manufacturing Systems (FMS) and leads to shorter working times and higher energy efficiency and annual profits. In addition, Pareto frontiers show the trade-off between profits and product manufacturing times for different case studies.

1. Introduction

Digital technologies are transforming the industrial landscape and disrupting traditional business models (Llopis-Albert et al., 2021a). In this sense, typical autonomous industrial processes encompass industrial robot arms and AGVs, which are programmable, self-driven vehicles used to transfer loads from one location in the facility to another depending on the given task and within a certain time window. AGVs can be considered as multiple systems that can operate independently as well as in cooperation with each other. They are increasingly attracting attention and are being rapidly adopted in many industrial and service applications. For instance, they are widely used in indoor transport tasks for Material Handling Systems (MHS) and multitask production planning.

This is due to the significant profits that companies gain from adequate deployment of automated technologies. These profits include an increase in the system's efficiency, a reduction in operational costs, and an increase in the precision of the work. They also help to design Flexible Manufacturing Systems (FMS) because of the ease with which the AGV network flow can be redesigned to accommodate frequent changes. In addition, the use of AGVs considerably reduces the number of work accidents related to transport and warehouse activities if compared with human operators. Note that occupational health and safety is a major concern nowadays. Furthermore, AGVs and industrial robot arms perform the production tasks at a lower cost than conveyors, chains, etc.

* Corresponding author.
E-mail address: frubio@mcm.upv.es (F. Rubio).

https://doi.org/10.1016/j.techfore.2021.121115
Received 26 May 2021; Received in revised form 3 August 2021; Accepted 11 August 2021
Available online 8 September 2021

Designing an AGV network flow entails efficient scheduling of operational tasks and routing schemes, traffic control schemes, and a proper definition of the allocation of stacking areas (Llopis-Albert et al., 2019). An AGV network flow is defined by open aisles between machines, workstations, allocation of stacking areas, departments, and fixed structures in the facility. A lane connecting a pair of nodes in the network can be classified as unidirectional, bidirectional, multi-lane, and mixed, and more than one lane can be defined in the same aisle if the traffic requirement is heavy. An appropriate AGV route must avoid collisions and minimize transportation times so that more tasks can be handled within a given time.

AGVs are usually battery powered and navigate along predefined guide-paths. This is carried out using different guidance technologies, which cover physical guide-paths such as tracking buried cables or guide-paths painted on the floor, optical sensors, laser navigation systems based on fixed reflectors located in the workplace, and magnetic and gyroscope-based inertial systems. These guidance technologies facilitate the re-routing process in response to changes made to the facility in order to provide FMS and scalable MHS.

An efficient design of an AGV system should take into account problems such as route design, traffic, battery management, determination of the fleet size, number and location of load/unload points, and number and location of idle points while considering possible fluctuations in demand and restrictions of machines integrated into AGV scheduling.

Algorithms have been developed to address routing and scheduling problems for AGVs. Two broad categories are distinguished: static and dynamic algorithms. The route with the static approach is determined in advance, which means the algorithms cannot adapt to changes in the logistic system and traffic conditions. In dynamic routing, on the other hand, the route is based on real-time information and, as a result, various routes between locations can be chosen.

AGV routing has been widely studied during recent decades. A literature review about this subject can be found in Bodin (1983), Psaraftis (1988; 1995), Laporte (1992), Fisher (1995), Kelly et al. (1999), and more recently in Pillac et al. (2013), Fazlollahtabar et al. (2015), and Llopis-Albert et al. (2018). Dynamic AGV scheduling and routing problems, including traffic conflicts and flexibility, mostly deal with optimizing network flow problems with a single objective (minimizing or maximizing the flow) or minimizing paths, but they fail to consider the kinematics and dynamics of the mobile robot. AGV routing has proven to be an NP-complete problem (Nishi et al., 2006), so approximate algorithms are used to find an optimal solution. They address the optimization problem using a wide range of mathematical models, such as heuristic and metaheuristic algorithms and exact solutions. Heuristic approaches take advantage of the problem's properties to derive solution strategies, while exact approaches seek global optimality but usually fail to provide appropriate solutions on NP-hard problems. For instance, Langevin et al. (1996) used a dynamic programming approach. Cordeau et al. (2002) dealt with the vehicle routing problem using time windows. Nishi et al. (2007) tackled the dynamic AGV routing problem using real-time data. Duinkerken et al. (2006) analyzed the problem of scheduling and conflict-free route allocation. Masae et al. (2020) proposed a Markov Chain (MC) approach to predict the probability of collisions and then recalculate the route. A hybrid mixed-integer programming approach has also been used (Corréa et al., 2007; Nishi et al., 2011; Kesen and Baykoç, 2007), tackling the allocation under a Just in Time (JIT) production using a bidirectional route flow. Zhang et al. (2008) used a Lagrangian relaxation approach. Nishi and Tanaka (2012) used a place/transition (Petri) net approach optimized by heuristics and obtained Petri net trajectories with conflict rules. Ghasemzadeh et al. (2009) also used a heuristic algorithm to tackle conflict-free bidirectional flows in the facility layout. Liu and Kulatunga (2007) analyzed the same problem by means of Simulated Annealing (SA) and an Ant Colony Optimization (ACO) algorithm. Chiew and Qin (2009) overcame traffic conflicts by using a concurrent bitonic algorithm. The genetic algorithm (GA) approach has been applied to minimize the trajectory time and maximize AGV use (Buyurgan et al., 2007; Udhayakumar et al., 2010; Umar et al., 2013). The Q-learning approach was applied by Jeon et al. (2011). Fazlollahtabar and Saidi-Mehrabad (2015) analyzed the uncertainty of production processes in a GA controlled by a feedback mechanism through fuzzy logic. Todosijevic et al. (2017) solved the vehicle routing problem using mixed-integer programming. A comprehensive review of the existing approaches for optimizing AGV systems can be found in Ramos et al. (2015).

The assessment of the effect of energy consumption on trajectories in AGVs and its relationship with sustainable measures for adaptation of the automotive industry to government pollutant emission regulations has been analyzed in Valero et al. (2019; 2019a), Rubio and Llopis-Albert (2019), Zheng et al. (2018), and Llopis-Albert et al. (2021b).

The importance of improving productivity for welding robots is also shown in Abolhassani et al. (2019) and Lin et al. (2019), where the authors analyze intelligent path optimization strategies to support optimal manufacturing logistics.

Additionally, an extensive review of optimization approaches for industrial robot trajectory planning is presented in Llopis-Albert et al. (2018). Furthermore, optimal time trajectories for industrial robots taking into account the energy consumed were studied by Rubio et al. (2012,2019a) and Llopis-Albert et al. (2015).

The present paper follows these research lines but goes a step further than the current literature by integrating a methodology into the framework of a multi-objective optimization algorithm to improve productivity and reduce the costs and energy consumption associated with autonomous industrial processes to achieve sustainable growth.

This paper is organized as follows: Section 2 introduces the optimization algorithm, while in Section 3, the methodology is applied to different case studies. In Section 4, the results are discussed. Finally, Section 5 presents the conclusions.

2. Material and methods

This section presents the multi-objective optimization algorithm used to conduct the study. It applies to a robotic cell composed of an industrial robot arm, a computer numerical control (CNC) machine tool, and an AGV (automatic guided vehicle) for in-plant transport and Material Handling Systems.

The framework presented combines several approaches, integrating and improving on previous developments by the authors of this paper. Firstly, the methodology integrates an algorithm that minimizes the working time of an industrial robot arm while taking into account the robot's kinematics and dynamics and the avoidance of collisions (Rubio et al., 2012; Llopis-Albert et al., 2015). Secondly, it also integrates trajectory planning for AGVs, respecting the dynamic constraints of the vehicle, including the characteristics of power delivery by the motor, the basic inertial parameters, and the behavior of the tires (Valero et al., 2019; 2019a). For the sake of conciseness, readers are referred to these works for a comprehensive explanation of such approaches; we only present a brief overview here. Basically, for the industrial robot, the algorithm takes into account the industrial robot kinematics and dynamics, boundary conditions (position, velocity, and acceleration) for initial, intermediate, and final configurations, collision avoidance within the robot workspace, physical limitations of the robot system (maximum torque, power, and jerk values are considered for each actuator), and the energy consumed.

AGVs are considered to have four wheels arranged symmetrically about their central axis, with the driving torque acting on the rear wheels, braking on all wheels, and front-wheel steering. Tire behavior is critical when determining the dynamic performance of the robot. The simplifying assumptions considered are that there are no roll and pitch motions and aerodynamic effects, there is no side load transfer, a bicycle-type planar model is used with three degrees of freedom, and a restriction is associated with the steering angle. The front and rear wheels are simplified and replaced by one that will account for the force exerted by both of them. The steering angle is equal for each front wheel and corresponds to the steering angle of the bicycle model. With the simplified dynamic model, the AGV performs safe, collision-free, feasible trajectories.

However, we detail the methodology for obtaining annual profits by a company that manufactures different products in the robotic cell, which undergo internal transport during the manufacturing process. Specifically, the products will be transported from the CNC machine tool to the warehouse. Let B be the function representing the annual profits, which is one of the two objectives in the multi-objective optimization problem. The intention is to maximize them as follows:

$$Max\, B \tag{1}$$

Which can be expressed as in Eq. (2):

$$B = A_o \cdot B_T - C_T \tag{2}$$

where:

A_o is the opportunity cost of investing money in the manufacture of product *m*.

B_T is the gross total profit of selling product *m* manufactured by the company.

C_T are the expenses associated with the internal transport of manufactured products.

A_o can be expressed as follows:

$$A_o = \frac{1}{(1+r)^T} \tag{3}$$

In Eq. (3), *r* is the annual interest, and *T* represents the number of years the company is productive. The total gross profit is:

$$B_T = \sum_{m=1}^{n} B_m \tag{4}$$

Where B_m is the gross profit of manufacturing product *m*. It can be expressed as follows:

$$B_m = \sum_{m=1}^{n} b_m \cdot Q_m \tag{5}$$

Where $b_m = P_m - C_m$ is the unit gross profit of manufacturing product *m*. It is obtained as the difference between the unit sale price P_m minus the unit cost of its production C_m.

Q_m is the number of each product *m* manufactured. It depends on the manufacturing time of each product. The shorter the time needed to manufacture a single unit of product m, the more products can be manufactured. It can be modeled as:

$$Q_m(t) = K_{1m} / t_{wm}(W_m)^{\gamma} \tag{6}$$

W_m represents the set of tasks necessary to manufacture one unit of product *m*, and t_{wm} is the time taken to manufacture one unit of product *m*.

$$t_{wm}(W_m) = t_{o\,m} + \sum_{i \in W_m} t_i \tag{7}$$

Times t_i include several concepts. One is the machining time of the raw product, which will depend on the number of operations *i* it undergoes (assuming that $i > 1$) and the duration of each operation. It also includes the time that the robot spends handling the product, which covers pick-up of the product from the AGV and drop-off in the machine and pick-up from the machine and drop-off again in the AGV once finished. The second objective of the multi-objective function is to minimize these times. As mentioned above, they are obtained by applying an auxiliary optimization algorithm that minimizes the working time (Rubio et al., 2012). The values of these optimized times are shown in Table 1. These times have also been used to carry out an economic study about the industrial robot's efficiency in an assembly line (Llopis-Albert et al., 2015). In addition:

Table 1
Robot working times for several examples.

Example	Robot manipulation time (s)	Example	Robot manipulation time (s)
1_1	3.79	4_1	18.28
1_2	22.55	4_2	14.51
1_3	19.27	4_3	10.69
1_4	25.76	4_4	18.28
2_1	5.14	4_5	14.51
2_2	5.15	4_6	10.69
2_3	5.3	4_7	8.49
2_4	5.62	4_8	6.74
2_5	6.42	4_9	3.21
2_6	12.25	4_10	2.41
2_7	21.08	4_11	18.65
2_8	23.05	4_12	9.94
2_9	26.35	5_3	3.08
3_1	2.27	5_4	9.18
3_2	7.34	5_5	15.91
3_3	14.82	5_6	15.93
3_4	17.94		

**(Each case study has been solved using different physical constraints associated with the robot actuators Nomenclature used. Example: numberexample_Number. Numberexample indicates the example solved, and the Number position indicates that the example has been solved using different constraints).

$t_{o\,m}$ crepresents the CNC machine's dead and stop times.

Constant K_{1m} represents the number of working hours per year available to manufacture product *m*.

Parameter γ takes into account the economic environment and the periods of maximum and minimum annual production. From Eq. (6), it follows that the less time spent by the robot and machine in manufacturing the product ($t_{wm}(W_m)$), the more products can be manufactured.

The following term is the cost associated with internal transport of the products. It can be modeled as follows:

$$C_T = p + A \cdot (t_{vm})^{K2} + \phi \tag{8}$$

Where *p* represents the internal transport expenses associated with the energy consumption and the proportional part of the costs pertaining to the AGVs used in the transport (insurance, repairs, maintenance, etc.). It can be expressed like this:

$$p = p_0 + H \cdot E_v \tag{9}$$

with p_0 being the fixed part of the expenses excluding the cost of energy, *H* the cost per unit of energy, and E_v the total energy used in internal transport by the vehicles. That is:

$$E_v = \sum_{i=1}^{m} E_{vm} \tag{10}$$

Where E_{vm} is the energy consumed in transporting product *m*. It depends on the number of units *n* manufactured. As explained, it is obtained by applying an auxiliary algorithm to optimize transport times and energy consumption of AGVs (Valero et al., 2019; 2019a). Several features have been considered to obtain the minimum time to perform a particular trajectory: the AGV dynamics, the location of the CNC machine tool and target location of the manufactured product, and the avoidance of collisions. In addition, the optimization problem is constrained by the dynamic parameters of the vehicle and its energy consumption. Table 2 shows the energy consumption for the cases studies analyzed in Section 3.

A is the unit value of travel time, which depends on the opportunity cost of using the AGV. It is also associated with the amortization value of the vehicle based on its useful life.

Table 2
AGV transport times and energy consumed for products A, B, and C between the initial and target location.

Product	Travel time (s)	Energy consumed (J)	Product	Travel time (s)	Energy consumed (J)
A_1	52.30	3380.11	B_7	39.66	8985.77
A_2	47.55	3979.47	B_8	39.71	9876.38
A_3	42.43	4997.35	B_9	38.32	10,164.40
A_4	37.91	5988.98	B_10	40.26	4494.28
A_5	43.51	6993.60	B_11	49.45	5494.90
A_6	35.30	7987.10	B_12	44.92	6475.10
A_7	35.82	7478.05	C_1	46.32	3389.20
A_8	35.97	9394.13	C_2	42.87	3974.28
A_9	35.15	7762.82	C_3	33.44	5000.57
A_10	40.14	4491.55	C_4	39.23	5911.38
A_11	35.40	5496.50	C_5	32.24	6730.44
A_12	49.96	6501.15	C_6	36.82	8008.51
B_1	57.83	3392.63	C_7	32.43	7226.96
B_2	44.00	3992.95	C_8	38.80	7500.77
B_3	45.68	4988.92	C_9	33.35	6391.90
B_4	40.98	5975.59	C_10	32.00	6506.95
B_5	42.66	6976.39	C_11	34.35	5479.18
B_6	36.99	7495.98			

*(Just one displacement for each product). Nomenclature used. Product: Typeofproduct_Number. Typeofproduct indicates the product analyzed (A, B, or C), the Number position indicates that the example has been solved using different constraints.

Parameter $K2$ considers the periods of inactivity of the AGV due to breakdowns, maintenance operations, lack of synchronization with the CNC machine tool, and other adverse events.

t_{vm} is the time taken to transport the n units of product m. If there are several routes to travel and each has a fixed distance, the time spent on each route is very important. This time spent is also minimized, thus reducing the costs associated with transport time. This value, tabulated in Table 2 for the examples analyzed, is obtained by applying an auxiliary optimization algorithm based on Sequential Quadratic Programming (SQP).

$$t_{vm} = t_{o\,v} + \sum_{k=1}^{n} t_k \tag{11}$$

where t_k is the time taken to cover path s to transport one unit (n have been manufactured) of product m. For the sake of simplicity, it will be considered that each unit of product m only undergoes a single transport.

Note that the times (t_{vm} and t_{wm}) are objectives that conflict with the other objective (i.e., profits B), because lower times lead to higher profits.

Finally, ϕ is a parameter that depends on qualitative aspects of transport. With equal prices and transport times, the factory managers can opt for different transport systems, using either an economy of scale or other motivations. In this work, its value will be considered negligible compared to the other two terms.

Finally, replacing expressions (2) to (11) in (1), the profit can be expressed as follows:

$$B = \frac{1}{(1+r)^T} \cdot \sum_{m=1}^{n} (P_m - C_m) \cdot \frac{K_1}{t_{wm}(W_j)^{\gamma}} - \left(p_0 + H \cdot E_v + A \cdot (t_{vm})^{K2}\right) \tag{12}$$

3. Application of the algorithm to different case studies

The methodology presented here has been applied to a robotic cell composed of a Puma 560 industrial robot, a CNC machine (that is capable of performing the operations programmed on the raw material to manufacture n units of different products m in a given time), and an AGV used for transporting both the raw material and the manufactured product (Fig. 1).

The robot picks up the raw material from the AGV and drops it off in the CNC machine tool. The machine works on it, performing the corresponding manufacturing processes that will give rise to 3 different products: A, B, and C (m= 3, whose key trait will be their weight and size). When the machine has finished, the robot picks up the manufactured product and drops it off in the AGV, which transports it to another point in the company's production line for subsequent operations. Fig. 2 shows the initial and target locations in the company facility.

The CNC machine tool and the Puma 560 robot are at the initial location (Fig. 2). Then the AGV moves the product to the target location (a different point of the production line).

The multi-objective optimization algorithm is applied to different case studies, which will be further defined in Section 4. The Pareto frontiers will be obtained in those case studies, which will allow us to obtain the trade-offs between the company's profit and production times. The production time includes the time taken by the industrial robot to manipulate the raw material, the manufacturing time in the CNC machine, and the product transportation times inside the facility using AGVs. Part of the process of maximizing the profits calculated by Eq. (12) is related to the time t_{vm} the robot takes to perform the tasks on product m. The shorter the time spent handling the pieces, the more pieces can be manufactured by the machine and, therefore, the greater the final profit. The different case studies entail three different types of products manufactured (m= 3), which spent a minimum working time in the robotic cell t_{vm} and a minimum internal transport time t_{vm} for each unit of each product. In general, the product working time is the sum of all the minimum times t_{vm} of each of the operations that each unit of product m undergoes:

Fig. 1. Elements working in the robotic cell.

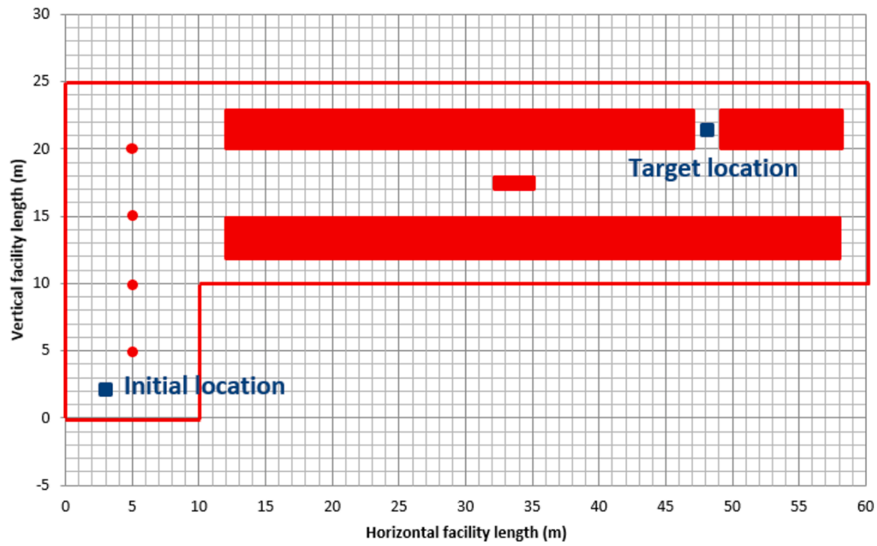

Fig. 2. Product Locations: Initial and Target locations.

$$t_{wm}(W_m) = t_{o\,m} + \sum_{i \in W_m} t_i \tag{13}$$

Also, the energy consumed will be considered by the algorithm for all the case studies.

4. Results and discussion

Table 1 shows the different times that the industrial robot spent handling the pieces for each case (under different operating characteristics, that is, different restrictions of the jerk value and energy consumed by the robot).

Similarly, the internal transport time is calculated according to expression (11):

$$t_{vm}(W_m) = t_{o\,v} + \sum_{k=1} t_k \tag{14}$$

The number of displacements that the products undergo is assumed to be one in this paper.

In short, the production of different products with different manufacturing times and internal transport times will give rise to different profits. The maximization of profits will largely depend on the optimization of manufacturing and transport times as well as the energy consumed.

Table 2 shows the transport times and the energy consumed for the three different products.

Fig. 3 depicts the optimized routes for three products (A_1, B_1, and C_1) and the facility layout. This result can help define the best facility layout to minimize AGV travel times.

Note that the values in Table 2 have been obtained by integrating a second auxiliary optimization algorithm based on previous works by the authors of this paper (Valero et al., 2019; 2019a) into the methodological framework presented here.

Next, the annual profit will be quantified using time optimization. To do this, the time difference between optimized and non-optimized processes will be assessed. Then, the profits (or losses) will be obtained using Pareto fronts.

Let us consider the time taken to manufacture products A_1, B_1, and C_1. The parameter values used in the multi-objective optimization algorithm are shown in Table 3. Considering that the market conditions do

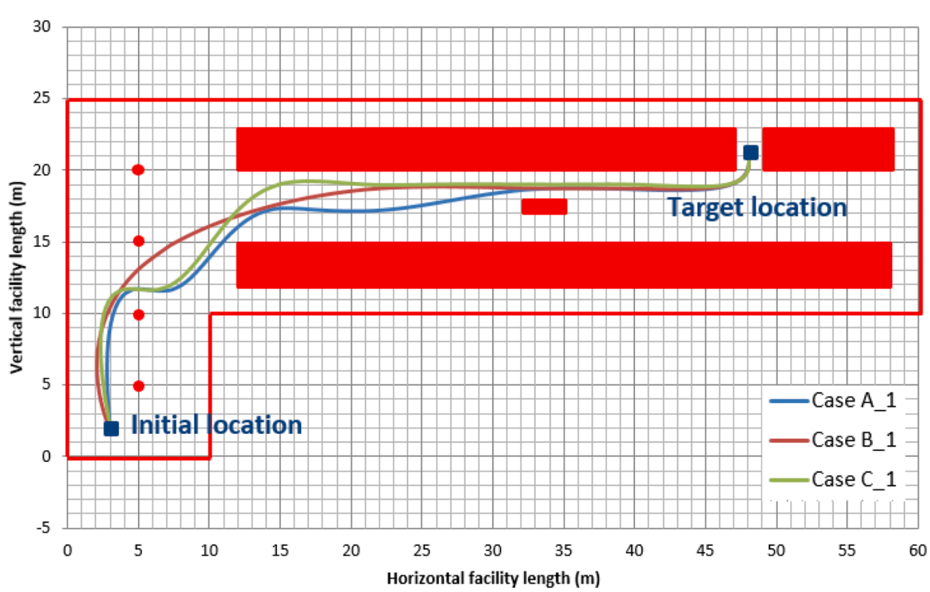

Fig. 3. Optimal trajectories for products A_1, B_1, and C_1.

Table 3
Parameters, industrial robot working times, and total times considering both manufacturing and transportation tasks.

	Product A	*Product B*	*Product C*
Execution time (s)	3.79	5.15	6.42
Fixed cost (€)	80	90	95
Product price (€)	105.29	112.34	131.47
Energy consumed by the robot arm (J)	87.5	90	93
Unitary energy cost of the robot arm (€)	1.6454E-06	1.6924E-06	1.7488E-06
Time taken by the other tasks (s)	12	14	17
Cumulative time of the robot arm (s)	15.5	19.15	23.42
Np (number of items manufactured)	18,940	20,113	13,981
Transport time, t_{vm} (s)	52.3	57.83	46.32
Energy consumed by transport (J)	3380.11	3392.63	3389.2
Energy cost of transport (€)	0.000063562	6.37975E-05	0.000063733
Fixed cost of transport (€)	0.25	0.27	0.29
Total cost (€)	89.98719	98.54536	106.88444
Total time (s)	67.3	76.98	69.74

not change and no optimization algorithm is used, there is a loss of profit because of the longer working times of the industrial robot arm and travel times of the AGVs.

Fig. 4 presents the Pareto frontier representing the trade-off between the decision variables, i.e., the profits and manufacturing times for different examples. Note that the optimization procedure leads to shorter working times and, therefore, greater annual profits.

The results for the three products clearly show that shorter times lead to greater profits since more products are produced within a particular shift. Moreover, the algorithm allows us to assess the loss of profits for longer times than those reported by the algorithm. This also shows the value of using the developed algorithm and the opportunity cost of not doing so.

Pareto optimality also depicts the opportunity cost of using longer than minimum manufacturing and transportation times. Additionally, it shows the trade-offs expressing the opportunity cost of one potential choice regarding which product to manufacture. Therefore, for a specific production time, the algorithm presented allows us to obtain the loss of profits if compared with the best alternative for manufacturing other products. For instance, for manufacturing times of around 60 s, it is better to manufacture product C than product A or product B.

This means that the Pareto front of Product C dominates the front of Products A and B, so higher profits are expected to be achieved for Product C. The difference in economic terms can reach a value of around €0.5 M. However, for longer times than 90 s, it is better to manufacture first product B, second product C, and third product A.

In this case, the difference regarding the decision to manufacture product B or C is negligible, but important if compared with product A. Note that for each product the algorithm can also take into account considerations such as its demand, the availability of raw materials, the transportation costs out the facility, the personnel on duty at each shift, etc. using a calibration process of the equation parameters presented in Section 2. Hence, the algorithm can deal with different economic environments, thus helping in the decision-making process for designing optimal production plans, adapting quickly to changes in the market, and assessing the financial suitability of each production alternative.

Fig. 5 presents the company's profits versus different product prices for product B and case 2 obtained by simulating a price fluctuation based on a normal distribution (with mean equal to the current price and standard deviation equal to one-tenth of the current price) due to different company strategies, economic environments, or market seasonality.

Likewise, Fig. 6 depicts the company's profits versus different product costs for product B and case 2 obtained by simulating a cost fluctuation based on a normal distribution (with mean equal to the current fixed cost and standard deviation equal to one-tenth of the current cost) due to changes in the market, costs of supplies, workforce, etc. These figures show how the algorithm allows us to determine the higher profits achievable by the company due to changes in the prices or costs of the products. This is because the algorithm returns the minimum times for both the executable times of the robot arm and the transportation time of the AGVs inside the facility.

Fig. 7 presents the annual profits for product A and several cases based on the current demand. It presents a wide range of company profits since they strongly depend on the particular variables that characterize each case. For example, case 1, which has no constraints in the jerk and the energy consumed by the robot arm, presents the highest

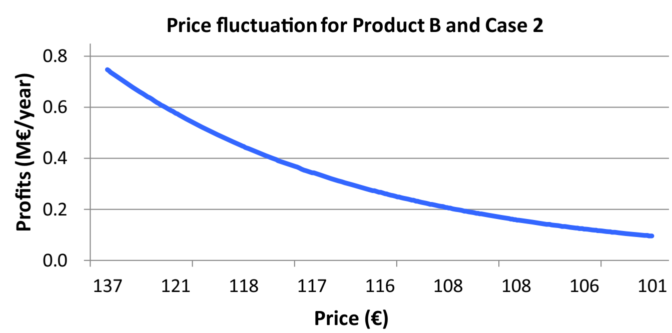

Fig. 5. Profits versus different product prices for product B and case 2 obtained by simulating a price fluctuation based on a normal distribution (with mean equal to the current price and standard deviation equal to one-tenth of the current price) due to different company strategies or economic environments.

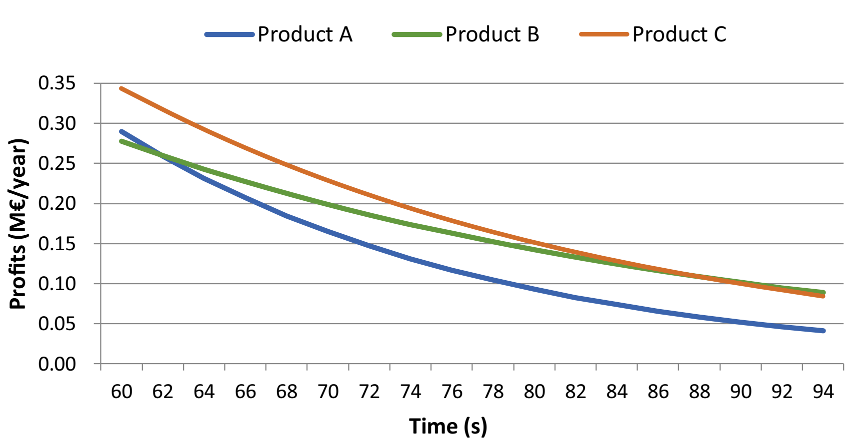

Fig. 4. Pareto fronts showing the trade-offs between the two objectives (i.e., profits and manufacturing time) for three different products.

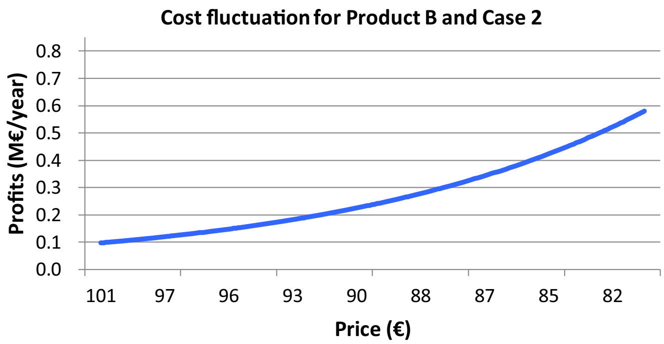

Fig. 6. Profits versus different product costs for product B and case 2 obtained by simulating a cost fluctuation based on a normal distribution (with mean equal to the current fixed cost and standard deviation equal to one-tenth of the current cost) due to changes in the market, costs of supplies or workforce, etc.

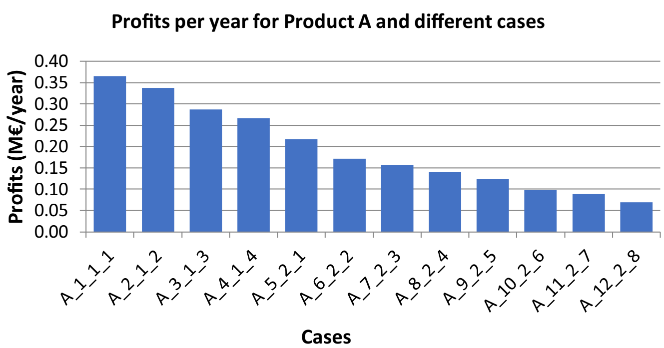

Fig. 7. Annual profits for product A and several examples based on the current demand. In the name of the cases, the first two digits refer to the industrial robot working times, and the last digit refers to the AGV travel time.

profits. On the contrary, case 5, with severe physical constraints, shows the lowest profits.

The differences between these three products are presented in Table 3, which shows the parameters used in the multi-objective optimization procedure, the industrial robot manipulating times, and the total times considering both manufacturing and transportation tasks.

In addition, the proposed algorithm could potentially be useful in further optimization studies and operational issues such as the detection of potential bottleneck points, deadlocks, idle times, and the possibility of collisions of the AGVs; the determination of how many AGVs are needed to meet the demand; the best scheduling in shifts, production, and maintenance tasks; and the network flow rules to maximize AGV utilization.

5. Conclusions

A multi-objective optimization algorithm under conflicting objectives is presented in order to optimize profits, working times, energy consumed, and trajectory followed by AGVs for the efficient warehousing of raw materials and finished products using a standard robotic system consisting of an industrial robot, a manufacturing machine, and an AGV under a flexible management environment. The algorithm also provides the trade-offs between decision variables using Pareto frontiers and a set of Pareto optimality solutions that satisfy the constraints.

The proposed algorithm can play an important role in factory logistics in terms of production efficiency and energy consumption. Furthermore, the algorithm ensures that AGVs operate with the required accuracy and provide the best possible performance.

Based on the manufacturing tasks carried out by the industrial robot arm and the manufacturing machine tool, the required transportation tasks between two locations in the facility, and the number of AGVs needed, the algorithm finds the minimum working and travel times, as well as the energy consumed, while taking into account economic issues such as the company's profits. It considers the kinematics and dynamics of the robot and AGV and obtains the minimum time to perform the robot tasks and the AGV's trajectories while avoiding collisions. In short, it optimizes productivity.

Several examples serve to assess this algorithm. They show that greater profits are achieved when this methodology is used since it leads to shorter working times and a higher number of products manufactured in a lower number of shifts. Additionally, the multi-objective optimization procedure and Pareto frontiers can help supervisors in the decision-making process, considering that product manufacturing, material handling, and efficient scheduling have a significant influence on the system's overall performance and reliability due to the direct impact on working and travel time, installation costs, and the complexity of the control system software. Warehousing management and improvements in on-time delivery can be enhanced, which are issues of major concern in a competitive market. Furthermore, reductions in energy consumption in autonomous industrial processes allow companies to design environmentally sustainable strategies that ensure compliance with governmental greenhouse gas (GHG) emission regulations and climate change mitigation and adaptation policies.

In future work, the limitations and simplifications used in the kinematic and dynamic model of autonomous industrial processes could be improved to make them more realistic. The algorithm could be improved by reducing the computational time for both the industrial robot and the AGVs when dealing with the obstacle collision avoidance system. Since they can be equipped with instrumentation to detect moving obstacles, the trajectories must be recalculated according to these moving obstacles, so it would be desirable to diminish computational times to work properly in real time.

CRediT authorship contribution statement

Francisco Rubio: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Investigation, Writing – review & editing. **Carlos Llopis-Albert:** Conceptualization, Methodology, Software, Data curation, Writing – original draft, Investigation, Writing – review & editing. **Francisco Valero:** Visualization, Supervision, Software, Validation, Writing – review & editing.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2021.121115.

References

Abolhassani, A., Harner, E.J., Jaridi, M., 2019. Empirical analysis of productivity enhancement strategies in the North American automotive industry. Int. J. Prod. Econom. 208, 140–159.
Bodin, L.D., 1983. Routing and scheduling of vehicles and crews: the state of the art. Comp. Oper. Res. 10 (2), 63–211.
Buyurgan, N., Meyyappan., L., Saygin, C., Dagli, C.H., 2007. Real-time routing selection for automated guided vehicles in a flexible manufacturing system. J. Manuf. Tech. Manage. 18, 169–181.
Chiew, K., Qin, S., 2009. Scheduling and routing of AMOs in an intelligent transport system. IEEE Trans. on Int. Transp. Sys. 10 (3), 547–552.
Cordeau, J.-.F., Desaulniers, G., Desrosiers, J., Solomon, M.M., Soumis, F., 2002. VRP with time windows. In: Toth, P., Vigo, D (Eds.), The Vehicle Routing Problem. SIAM Monographs on Discr, Math. Applic., pp. 157–193
Corréa, I., Langevin, A., Rousseau, .L.-M., 2007. Scheduling and routing of automated guided vehicles: a hybrid approach. Comp. Oper. Res. 34, 1688–1707.
Duinkerken, M.B., Ottjes, J.A., Lodewijks, G., 2006. Comparison of routing strategies for AGV systems using simulation. Proceed. Winter Simul. Confer. 1523–1530.
Fazlollahtabar, H., Mahdavi-Amiri, N., 2015. Producer's behavior analysis in an uncertain bicriteria AGV-based flexible jobshop manufacturing systems with expert system. Intern. J. Manufact. Tech. 65, 1605–1618.

Fazlollahtabar, H., Saidi-Mehrabad, M., 2015. Autonomous guided vehicles: methods and models for optimal path planning. Springer. ISBN 978-3-319-14747-5. 10.1007/978-3-319-14747-5.
Fisher, M., 1995. Vehicle routing (eds.). In: Ball, M.O., Magnanti, C.L., Monma, C.L., Nemhauser, G.L (Eds.), Network Routing. Elsevier, Amsterdam, pp. 1–33.
Ghasemzadeh, H., Behrangi, E., Azgomi, M.A., 2009. Conflict-free scheduling and routing of automated guided vehicles in mesh topologies. Robot. Auton. Syst. 57 (6–7), 738–748.
Jeon, S.M., Kim, K.H., Kopfer, H., 2011. Routing automated guided vehicles in container terminals through the Q-learning technique. Logist. Res. 3 (1), 19–27.
Kelly, J.P., Xu, J., 1999. A set-partitioning-based heuristic for the vehicle routing problem. J. Comput. 11 (2), 161–172.
Kesen, S.E., Baykoç, Ö.F., 2007. Simulation of automated guided vehicle (AGV) system based on just-in-time (JIT) philosophy in a job-shop environment. Simul. Model. Pract. Theo. 15 (3), 272–284.
Langevin, A., Lauzon, D., Riopel, D., 1996. Dispatching, routing, and scheduling of two automated guided vehicles in a flexible manufacturing system. Intern. J. Flex. Manufact. Syst. 8, 247–262.
Laporte, G., 1992. The vehicle routing problem: an overview of exact and approximate algorithms. Europ. J. Operat. Res. 59 (3), 345–358.
Liu, D.K., Kulatunga, A.K., 2007. Simultaneous planning and scheduling for multi-autonomous vehicles. eds.. In: Dahal, K.P., Tan, K.C., Cowling, P.I. (Eds.), Evolutionary Scheduling. Springer-Verlag, Heidelberg, pp. 437–464.
Lin, J., Naim, M.M., Spiegler, V.L., 2019. Delivery time dynamics in an assemble-to-order inventory and order based production control system. Intern. J. Prod. Econom. 223, 107531.
Llopis-Albert, C., Rubio, F., Valero, F., 2015. Improving productivity using a multi-objective optimization of robotic trajectory planning. J. Bus. Res. 68 (7), 1429–1431. https://doi.org/10.1016/j.jbusres.2015.01.027.
Llopis-Albert, C., Rubio, F., Valero, F., 2018. Designing efficient material handling systems via automated guided vehicles (AGVs). Multidis. J. Edu., Soc. Tech. Sci. 5 (2), 97–105, 10.4995/muse.2018.10722.
Llopis-Albert, C., Rubio, F., Valero, F., 2019. Fuzzy-set qualitative comparative analysis applied to the design of a network flow of automated guided vehicles for improving business productivity. J. Bus. Res. 101, 737–742, 10.1016/j.jbusres.2018.12.076.
Llopis-Albert, C., Rubio, F., Valero, F., 2021a. Impact of digital transformation on the automotive industry. Technol. Forecast. Soc. Change 162, 120343, 10.1016/j.techfore.2020.120343.
Llopis-Albert, C., Palacios-Marqués, D., Simón-Moya, V., 2021b. Fuzzy set qualitative comparative analysis (fsQCA) applied to the adaptation of the automobile industry to meet the emission standards of climate change policies via the deployment of electric vehicles (EVs). Technol. Forecast. Soc. Change 169, 120843. https://doi.org/10.1016/j.techfore.2021.120843.
Masae, M., Glock, C.H., Grosse, E.H., 2020. Order picker routing in warehouses: a systematic literature review. Internat. J. Product. Econom. 224, 107564.
Nishi, T., Ando, M., Konishi, M., 2006. Experimental Studies on a local rescheduling procedure for dynamic routing of autonomous decentrelized AGV systems. Robot. Comput. Integrat. Manufact. 22, 154–165.
Nishi, T., Hiranaka, Y., Grossmann, I.E., 2011. A bilevel descomposition algorithm for simultaneous production scheduling and conflict-free routing for automated guided vehicles. Comput. Operat. Res. 38, 876–888.
Nishi, T., Tanaka, Y., 2012. Petri net decomposition approach for dispatching and conflict-free routing of bidirectional automated guided vehicle systems. IEEE Transact. Syst. Man Cybernet. Part A: Systems and Humans. 42 (5), 1230–1243.
Nishi, T., Morinaka, S., Konishi, M., 2007. A distributed routing method for AGVs under motion delay disturbance. Robot. Comput. Integrat. Manufact. 23, 517–532.
Pillac, V., Gendreau, M., Guéret, C., Medaglia, A.L., 2013. A review of dynamic vehicle routing problems. Europ. J. Operat. Res. 225 (1), 1–11.
Psaraftis, H., 1988. Dynamic vehicle routing problems. editors. In: Golden, B.,, Assas, A. (Eds.), Vehicle Routing: Methods and Studies. Elsevier Science Publishers B.V, Amsterdam, Netherlands 1043 NX, pp. 223–248.
Psaraftis, H.N., 1995. Dynamic vehicle routing: status and prospects. Ann. Oper. Res. 61 (1), 143–164.
Ramos, I., Romero, L.F., Martínez, J.L., Olivares, E., 2015. Review of comprehensive approaches in optimizing AGV systems. operational excellence in logistics and supply chains. Thorsten Blecker, Wolfgang Kersten and Christian M. Ringle (Eds.), GmbH. ISBN: 978-3-7375-4058-2.
Rubio, F., Valero, F., Sunyer, J.L., Cuadrado, J.I., 2012. Optimal time trajectories for industrial robots with torque, power, jerk and energy consumed constraints. Indust. Robot: Internat. J. 39 (1), 92–100.
Rubio, F., Llopis-Albert, C., 2019. Viability of using wind turbines for electricity generation in electric vehicles. Multidis. J. Educ., Soc. Tech. Sci. 6 (1), 115–126, 10.4995/muse.2019.11743.
Rubio, F., Llopis-Albert, C., Valero, F., Besa, A., 2019a. Sustainability and optimization in the automotive sector for adaptation to government vehicle pollutant emission regulations. J. Bus. Res. 10.1016/j.jbusres.2019.10.050.
Todosijevic, R., Hanafi, S., Uroševic, D., Jarboui, B., Gendron, B., 2017. A general variable neighborhood search for the swap-body vehicle routing problem. Comput. Operat. Res. 78, 468–479.
Udhayakumar, P., Kumanan, S., 2010. Task scheduling of in FMS using non-traditional optimization techniques. Internat. J. Sim. Model. 9 (1), 28–39.
Umar, U.A., Ariffin, M.K.A., Ismail, N., Tang, S., 2013. Conflict-free automated guided vehicles routing using multi-objective genetic algorithm. Res. J. Appl. Sci., Eng. Technol. 6 (14), 2681–2684.
Valero, F., Rubio, F., Llopis-Albert, C., 2019. Assessment of the effect of energy consumption on trajectory improvement for a car-like robot. Robotica 37 (11), 1998–2009, 10.1017/S0263574719000407.
Valero, F., Rubio, F., Besa, A., Llopis-Albert, C., 2019a. Efficient trajectory of a car-like mobile robot. Industr. Robot. 46 (2), 211–222, 10.1108/IR-10-2018-0214.
Zhang, M., Batta, R., Nagi, R., 2008. Modeling of workflow congestion and optimization of flowrouting in manufacturing/warehouse facility. Managem. Sci. 5 (2), 267–280, 5.
Zheng, X., Lin, H., Liu, Z., Li, D., Llopis-Albert, C., Zeng, S., 2018. Manufacturing decisions and government subsidies for electric vehicles in China: a. Maximal Social Welfare Perspective. Sustainability 10 (3), 672, 10.3390/su10030672.

Francisco Rubio received the Ph.D. degree in mechanical engineering from the Universitat Politècnica de València, Spain, in 2007. Currently, he is an associate professor at UPV, Spain. His-current research topics are optimization techniques, vehicle dynamics and environmental issues. He is author of other papers related to those topics.

Carlos Llopis-Albert received the Engineer Degree in Mechanical Engineering from the Universitat Politècnica de València (UPV), Spain, and the PhD in the same university. Currently he is an associate professor at the Mechanical Engineering department and his research focus on optimization techniques, vehicle dynamics and environmental issues.

Francisco Valero received the Ph.D. degree in mechanical engineering from the Universitat Politècnica de València, Spain, in 1990. Currently, he is an associate professor, UPV, Spain. His-current research interest lies in the areas optimization techniques, vehicle dynamics and environmental issues.