A comparative approach of single-objective optimization algorithms for energy control of flexible manufacturing system

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Abstract: This study presents a comparative analysis of the effectiveness of single-objective algorithms in optimizing automated process control. The research is conducted on a flexible manufacturing system (FMS) comprising seven production stations, each equipped with an energy consumption monitoring system. The objective is to examine how the optimization algorithms can contribute to enhancing the operational efficiency of the production systems. The study evaluates several single-objective algorithms – Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO), Ant Colony Optimization (ACO) to assess their potential for energy optimization in flexible manufacturing processes on FMS. Each algorithm's strengths and limitations are discussed with respect to their effectiveness in minimizing energy consumption and enhancing system performance. A comparative evaluation of the results obtained through the implementation and testing of each algorithm highlighted the superiority of the GWO algorithm.

Keywords: Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO), Ant Colony Optimization (ACO), Flexible Manufacturing System (FMS).

O abordare comparativă a algoritmilor de optimizare cu un singur obiectiv pentru controlul energetic al unui sistem flexibil de fabricație

Rezumat: Acest studiu prezintă o analiză comparativă a eficacității algoritmilor cu obiectiv unic în optimizarea controlului automat al proceselor. Cercetarea este efectuată pe un sistem flexibil de fabricație (FMS) alcătuit din șapte stații de producție, fiecare echipată cu un sistem de monitorizare a consumului de energie. Obiectivul este de a analiza modul în care algoritmii de optimizare pot contribui la creșterea eficienței operaționale a sistemelor de producție. Studiul evaluează mai mulți algoritmi cu un singur obiectiv precum Algoritmi Genetici (GA), Optimizarea Roiului de Particule (PSO), Optimizarea Lupului Gri (GWO), Optimizarea Coloniilor de Furnici (ACO) pentru a analiza potențialul de optimizare al consumului de energie în procesele de fabricație flexibile implementate pe FMS. Punctele forte și limitările fiecărui algoritm sunt discutate în raport cu eficacitatea acestora în minimizarea consumului de energie și îmbunătățirea performanței sistemului. Evaluarea comparativă a rezultatelor obținute prin implementarea și testarea fiecărui algoritm a evidențiat superioritatea algoritmului GWO.

Cuvinte-cheie: Algoritm Genetic (GA), Optimizare Roi de Particule (PSO), Optimizare Lupi Gri (GWO), Optimizare Colonii de Furnici (ACO), Sistem Flexibil de Fabricație (FMS).

1. Introduction

Flexible Manufacturing System (FMS) represent an advanced manufacturing paradigm designed to enhance production efficiency and adaptability. They consist of interconnected machines, workstations, and transport systems that work cohesively to produce a variety of

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products with minimal manual intervention. FMS are characterized by their ability to quickly adjust to changes in product type and volume, making them highly suitable for the environments where the market demands are dynamic and diverse (Košťál & Delgado, 2013).

Advanced data analytics and artificial intelligence (AI) are transformative technologies within Industry 4.0 that enhance the capabilities of FMS. By applying machine learning algorithms and predictive analytics, manufacturers can forecast demand, detect anomalies, and optimize production schedules (Knežević, Blagojević & Ranković, 2023). AI-driven systems can analyse vast amounts of data to identify patterns and trends, enabling proactive adjustments to the production processes and improving the overall efficiency.

When aiming to optimize the production process, the use of software solutions that enable modelling, simulation, and optimization of the production process is essential, given their enhanced capabilities for analysing large volumes of data. This necessitates the development of mathematical models that closely resemble real-world systems. These models facilitate the simulation of industrial system behaviour, enabling the exploration of various production scenarios, the comparison of the outcomes, and the implementation of the most efficient scenario based on the variables of interest. The approach to reducing the energy consumption required for the production processes can be achieved by integrating the technologies introduced with the advent of Industry 4.0 and Industry 5.0, alongside the methodologies specific to the energy management (Alexandru et al., 2023).

This article aims to achieve the following objectives:

- **O1.** Present the current state of the laboratory flexible manufacturing system (FMS) as a hardware structure adapted to parallel flow manufacturing, but also to collaborative tasks concepts;
- **O2.** Develop and apply mathematical models within the single-objective optimization algorithms for the optimized control of speed and displacement in the work-in-progress products;
- **O3.** Compare the results obtained for each applied algorithm and identify the algorithm with the highest efficiency for the analysed process.

To achieve these objectives, the paper is structured into the following chapters: Introduction, Literature Review, Experimental Setup, Results and Discussion, and Conclusions. In the Literature Review chapter, various algorithmic approaches applied to the production processes, discussed in relevant articles, are considered. The Experimental Setup and Tests section presents the flexible manufacturing system on which the tests will be conducted, along with the data acquisition system and the method of implementing the algorithms. In the Results and Discussion chapter, the analysed algorithms are evaluated from a performance perspective. Finally, the Conclusions section offers a general assessment of the research conducted.

2. Literature review

Optimization techniques like Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Gray Wolf Optimizer (GWO) are widely used in manufacturing to enhance various aspects of production processes. Each technique has its unique approach and advantages.

2.1. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) proposed by Kennedy and Eberhart (Kennedy & Eberhart, 1995) is a population-based optimization algorithm inspired by the social behaviour of birds and fish. It involves a group of candidate solutions of particles, which move around in the search space to find the optimal solution. Each particle adjusts its position based on its own experience and that of its neighbours (Dinu, 2015).

PSO is an algorithm that involves the movement of particles within a search space. To find the optimal solution, PSO integrates two components: the particle's position and velocity. These components govern the algorithm's ability to explore and exploit the search space. The most promising value for each particle is stored in a variable named p, while the best value identified by any particle is retained in a variable named g. Therefore, for improved efficiency, the algorithm must constantly update the particles velocities to facilitate the optimal exploration and convergence (Yunus & Alsoufi, 2020):

$$v_l^{(k+1)} = \omega * v_l^{(k)} + c_1 * r_1 * (p_l - x_l^{(k)}) + c_2 * r_2 * (g - x_l^{(k)}) \quad (1)$$

where: ω represents the value that balances the exploration and exploitation within the algorithm; c_1 is the attraction coefficient towards position *p*; c_2 is the attraction coefficient towards position *g*; r_1 and r_2 are random values within the interval $[0,1]$ (Ghulman & Yunus, 2021).

The position of each particle is updated at each iteration of the algorithm:

$$x_l^{(k+1)} = x_l^{(k)} + v_l^{(k+1)} \quad (2)$$

In production scheduling, PSO can be used to optimize the job scheduling for minimizing the total time required to complete a set of jobs and maximizing the machine utilization. For example, consider a manufacturing facility with multiple machines and a set of jobs that need to be processed. The objective is to find the optimal jobs sequence on each machine to minimize the total production time and meet the delivery deadlines.

A study by Zhen Wang, Jihui Zhang, Shengxiang Yang (2019) applied PSO to optimize job scheduling in a flexible manufacturing system. The researchers formulated the job-shop scheduling problem as a combinatorial optimization problem and used PSO to find the optimal schedule. The PSO algorithm was able to efficiently generate near-optimal schedules, reducing the makespan and improving machine utilization compared to the traditional scheduling methods (Wang, Zhang & Yang, 2019).

The research (Verdejo et al., 2020) presents an innovative method for optimizing the tuning of the Power System Stabilizer (PSS) in complex electric power systems with multiple machines. The study proposes a PSO-based methodology designed to optimize the parameters of PSS to ensure system stability and improve the damping of oscillations in large-scale multimachine electric power systems. The novelty lies in the application of the PSO within DigSilent PowerFactory, a widely used commercial simulation software, which enhances the practical applicability of the paper.

The research (Mishra & Sahu, 2018) focuses on improving the efficiency and performance of manufacturing systems by optimizing machine combinations using the Particle Swarm Optimization (PSO) technique. PSO, a computational method inspired by the social behaviour of birds and fish, is used to minimize bottlenecks, reduce idle times, and enhance the overall production efficiency in manufacturing environments. The study seeks to determine the optimal combination of machines in a manufacturing cluster to avoid conditions, such as buffering and bottlenecks, that reduce production efficiency. The researchers develop a mathematical model representing the manufacturing process, incorporating machine productivity, reliability, and performance metrics. The PSO is employed to optimize this mathematical model by iteratively refining solutions (machine combinations) and improving the overall system performance. The optimized machine combination proposed by the PSO leads to a significant improvement in efficiency (from 66% to 74%), a reduction in production time per unit, and a decrease in installation costs.

The article (Vukojičić & Veinović, 2022) investigates the use of the Particle Swarm Optimization (PSO) to enhance the multimodal trait prediction. By addressing the limitations of the traditional prediction methods, the study demonstrates that the PSO effectively navigates complex, high-dimensional search spaces. The authors conduct extensive experiments, revealing significant improvements in prediction accuracy and robustness compared to the conventional approaches.

This research contributes valuable insights for applying the PSO in various fields, such as psychology and marketing, where an accurate trait assessment is very important.

In their study (Yu et al., 2019) the authors Yang Yu, Lin Kong, Yanju Liu, and Jianhui Song investigate an advanced method for pedestrian detection in far-infrared imagery. They propose a novel approach that utilizes the Particle Swarm Optimization (PSO) to optimize the parameters of the Support Vector Machine (SVM) classifiers, specifically targeting the challenges posed by the low-contrast and low-resolution infrared images. The research demonstrates that the integration of the PSO enhances the effectiveness of the SVM by accurately determining the optimal values for crucial parameters, such as the penalty factor and Gaussian kernel parameter. The experimental results show a significant improvement in the detection accuracy, showcasing the potential of this methodology for real-time applications in safety-critical environments, such as the autonomous vehicles.

2.2. Genetic Algorithms (GA)

The Genetic Algorithms, first developed by John Holland (Holland, 1984), can be applied to optimize the facility layout design by determining the most efficient arrangement of the machines, workstations, and storage areas, with the goal of minimizing material handling costs and improving workflow. This process generates an initial population, referred to as $A_1 = (a_{1,1}, a_{1,2}, a_{1,3}, ..., a_{1,n})$, which is randomly selected from the state space. The selection is based on the fitness function, and the selection probability, Pi, can be computed using the following formula:

$$A(X_a) = \frac{f(X_a)}{\sum_{b=1}^{n} X_b} \tag{3}$$

The crossover is a technique used to combine two solutions in order to generate a potentially better solution (Gao et al., 2021). There are several types of crossovers, including: Single-Point Crossover, Two-Point Crossover, Uniform Crossover, Arithmetic Crossover, Blend Crossover (BLX-α), and Heuristic Crossover. Typically, the choice of the crossover type depends on the specific optimization problem being addressed.

Single-point crossover approach, two parent solutions: $A_1 = (a_{1,1}, a_{1,2}, a_{1,3}, ..., a_{1,n})$ and $A_2 = (a_{2,1}, a_{2,2}, a_{2,3}, ..., a_{2,n})$. If point b is selected as the crossover point, then the offspring generated in the next generation will inherit a combination of traits from each parent up to and beyond this point, resulting in a distinct architecture for each child: $A_1 = (a_{1,1}, a_{1,2}, ..., a_{1,b}, a_{2,b+1}, ..., a_{2,n})$ and $A_1 = (a_{2,1}, a_{2,2}, ..., a_{2,b}, a_{1,b+1}, ..., a_{1,n})$. In the uniform crossover it is considered that: for each gene at position *k*, the parent can generate offspring: $O_1[k] = a_{1,k}$ and $O_2[k] = a_{2,k}$ or $O_1[k] = a_{2,k}$ and $O_2[k] = a_{1,k}$ based on a probability of 0.5.

The paper (Mak, Wong & Chan, 1998) explores the application of the genetic algorithms to solve the complex facility layout problems (FLP) in manufacturing systems. The research develops a mathematical model that examines the layout of machines and the pattern of material flow, particularly in the job shop and flow shop environments. The study addresses several practical considerations, such as space constraints, irregular plant shapes, and reserved machinery locations, to find the optimal solutions.

The Genetic Algorithms are also extensively used in production scheduling, where the goal is to determine the optimal sequence of operations to maximize the efficiency, minimize the cycle time, or reduce the production costs. GA is particularly suited for scheduling problems with multiple objectives and constraints (Mak, Wong & Chan, 1998).

The paper (Wang et al., 2021) presents a comprehensive study on optimizing disassembly line balancing (DLB) through an enhanced multi-objective genetic algorithm (MOGA). The authors, Wang et al., identify five critical objectives, including minimizing the number of workstations, balancing idle time, prioritizing hazardous component disassembly, and optimizing the directional changes during the disassembly. By applying the proposed MOGA to real-world disassembly scenarios, the research demonstrates improved efficiency in line balancing, highlighting the algorithm's effectiveness in addressing uncertainties inherent in the disassembly processes.

In the article (Didden et al., 2022), the authors address the complexity of the assembly line balancing in the automotive production, a critical process for maximizing the efficiency. They propose a genetic algorithm (GA) that automates the job distribution across the assembly lines, effectively considering factors such as mixed-model production, sequence-dependent setup times, and variable workplaces. Through extensive testing on real-world scenarios, the study shows that the GA significantly improves the assembly line efficiency and reduces the variance in the operating time among different model variants. The results underscore GA’s potential as a decision support system, offering a streamlined approach to tackling the challenges of the modern automotive assembly.

The paper (Gen, Cheng & Oren, 2001) by Mitsuo Gen, Runwei Cheng, and Shumuel Oren, explores the use of the genetic algorithms (GAs) in optimizing various network design problems. These include challenges like the minimum spanning tree, fixed-charge transportation, and local area network (LAN) designs. The study presents an advanced GA methodology that adapts well to the dynamic and complex requirements of the network design, demonstrating significant improvements in the efficiency and problem-solving capabilities.

2.3. Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is an optimization algorithm based on the foraging behaviour of ants. In nature, ants find the shortest paths to food sources by laying down pheromones, which guide other ants. In ACO, artificial ants simulate this behaviour to solve computational problems, especially optimization challenges. The algorithm uses probabilistic techniques to explore and exploit potential solutions by iteratively improving based on pheromone trails, allowing efficient path discovery in complex search spaces. ACO is widely used for combinatorial optimization problems due to its adaptability and robustness. The ACO algorithm incorporates the concept of graphs to solve optimization problems. In this framework, each ant can choose a path based on the pheromone level left by other ants as well as on the visibility of the nodes. The pheromone level represents the intensity of the desire to move from one node to another. The probability of moving from node l to node k is given by the following relation:

$$P_{l,k}^{t} = \frac{(\tau_{lk})^{\alpha} * (\eta_{lk})^{\beta}}{\sum_{y \in allowedt} (\tau_{ly})^{\alpha} * (\eta_{ly})^{\beta}} \tag{4}$$

where: $P_{l,k}^{t}$ the probability of moving to the node, τ_{lk} the pheromone level between nodes l and k, η_{lk} the desire to move from node l to node k, α controls the influence of the pheromone level, β controls the influence of desirability, *allowed_t* represents the nodes that ant *t* has not yet visited.

At each iteration, the algorithm updates the pheromone levels through two operations: pheromone deposition and pheromone evaporation. The evaporation allows the reduction of the pheromone levels to prevent the algorithm from converging to suboptimal solutions. The pheromone evaporation process is mathematically modelled as follows:

$$\tau_{lk} \leftarrow (1-\rho) * \tau_{lk} \quad \rho \in (0,1) \tag{5}$$

where: $\rho \in (0,1)$ represents the pheromone evaporation process, and the interval allows for either slow or rapid evaporation, depending on the quality of the identified solution.

The pheromone deposition enables the identification of the optimal solution, and the ranking of the solutions based on their quality. The pheromone deposition process is mathematically represented as follows:

$$\Delta\tau_{lk}^{t} = \begin{cases} \dfrac{Q}{L^{t}} \\ 0 \end{cases} \tag{6}$$

where: $\frac{Q}{L^t}$ handles the situation where ant t is on an edge l, k, and 0 in any other situation, Q is a constant and L^t represents the cost of the path constructed by ant t.

The paper (Dorigo, Birattari & Stutzle, 2006) by Dorigo, Birattari, and Stutzle, offers an in-depth exploration of the Ant Colony Optimization (ACO) metaheuristic. ACO, inspired by the foraging behaviour of real ants, is a powerful algorithmic framework used to tackle combinatorial optimization problems. The authors detail the algorithm's structure, where artificial ants build solutions based on pheromone trails that guide them toward the optimal problem-solving routes. The paper also highlights several applications of the ACO, including its efficacy in solving the traveling salesman problem and other complex network optimization challenges.

The paper (Kılıçaslan et al., 2023) by Emre Kılıçaslan, Halil Ibrahim Demir, Abdullah Hulusi Kökçam, Rakesh Kumar Phanden and Caner Erden, explores the use of the Ant Colony Optimization (ACO) in solving the bottleneck station scheduling problems. The study aims to improve the efficiency of the production systems by optimizing schedules at the bottleneck stations, which are critical points in the workflow that can significantly affect the overall production times. Through simulations and real-world data, the research demonstrates that ACO is highly effective in balancing the workload and reducing delays at the bottleneck stations. The algorithm's ability to adaptively find the optimal paths by simulating the behaviour of ants searching for food, proves useful for minimizing the bottleneck effects and enhancing the production throughput.

The article (Paprocka, Krenczyk & Burduk, 2021) by Iwona Paprocka, Damian Krenczyk and Anna Burduk, explores the application of the Ant Colony Optimization (ACO) for the production scheduling under uncertain conditions. The study addresses challenges in the dynamic production environments, where uncertainties like machine breakdowns, or fluctuating job times can disrupt the schedules. The authors propose a method that leverages the adaptive and decentralized nature of the ACO to generate flexible production schedules which are robust against uncertainties.

The paper (Kato, Morandin & Fonseca, 2009) addresses the use of Ant Colony Optimization (ACO) for tackling reactive scheduling issues in the job shop systems. The study focuses on developing a robust ACO-based approach to dynamically reschedule jobs in response to disruptions like machine breakdowns or order changes, ensuring that the production remains efficient despite unexpected events. The algorithm adapts to changes in real-time, helping optimize the workflow and minimize delays in a highly variable production environment.

The paper (Wu, Zhang & Zhu, 2012) investigates the application of the Ant Colony Optimization (ACO) for optimizing master production scheduling (MPS). The authors focus on improving the efficiency and accuracy of the MPS, which is critical for balancing the demand and production capacity in the manufacturing systems. By employing ACO, the algorithm searches for the optimal scheduling solutions by mimicking the behaviour of the ants searching for food, ensuring that the production plans are feasible, cost-effective and responsive to the changing demands.

2.4. Gray Wolf Optimization (GWO)

The Gray Wolf Optimization (GWO) is a nature-inspired optimization algorithm that mimics the leadership hierarchy and hunting behaviour of grey wolves in the wild. Developed by Mirjalili et al. in 2014 (Mirjalili, S., Mirjalili, S.M. & Lewis, 2014), GWO is known for its simplicity and effectiveness in solving complex optimization problems. The algorithm involves four types of wolves (alpha, beta, delta, and omega) that guide the search process towards the optimal solution, balancing exploration and exploitation. GWO has been successfully applied in various manufacturing contexts to optimize processes, improve efficiency, and reduce costs (Kulkarni, O. & Kulkarni, S., 2018).

The Grey Wolf Optimization (GWO) algorithm incorporates the hierarchical structure of *alpha, beta, and delta* wolves to effectively identify the optimal solution. This hierarchy guides the search process, with wolves moving iteratively by updating their positions within the solution space. The movement of wolves follows a mathematical model designed to simulate their natural hunting strategies, allowing the algorithm to converge toward the best possible solution:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} + \overrightarrow{X_\alpha} + \vec{X}\right| \quad \overrightarrow{D_\beta} = \left|\overrightarrow{C_2} + \overrightarrow{X_\beta} + \vec{X}\right| \quad \overrightarrow{D_\delta} = \left|\overrightarrow{C_3} + \overrightarrow{X_\delta} + \vec{X}\right| \tag{7}$$

where: $\vec{X}$ represents the position of the current wolf; $\overrightarrow{X_\alpha}, \overrightarrow{X_\beta}, \overrightarrow{X_\delta}$ represent the positions of the wolves that have identified the best solutions and $\overrightarrow{C_1}, \overrightarrow{C_2}, \overrightarrow{C_3}$ are used to balance the exploitation and exploration phases of the search process.

Each wolf updates its position based on the average of the three leading wolves (*alpha, beta, and delta*):

$$X(k+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{8}$$

$$\overrightarrow{X_1} = \left|\overrightarrow{X_\alpha} - \overrightarrow{A_1} * \overrightarrow{D_\alpha}\right| \quad \overrightarrow{X_2} = \left|\overrightarrow{X_\beta} - \overrightarrow{A_1} * \overrightarrow{D_\alpha}\right| \quad \overrightarrow{X_3} = \left|\overrightarrow{X_\delta} - \overrightarrow{A_1} * \overrightarrow{D_\alpha}\right| \tag{9}$$

The vectors A and C serve as coefficients that control the exploration behaviour of the wolves, influencing how they search the solution space as follows:

$$\vec{A} = 2 * \vec{a} * \vec{r} - \vec{A} \quad \vec{C} = 2 * \vec{r} \tag{10}$$

where: $\vec{a}$ is a linearly decreasing vector with values in the interval (0,2) and $\vec{r}$ is a random vector with values in the interval [0,1].

In manufacturing, the optimizing process parameters are critical for improving the product quality, reducing waste, and enhancing the overall efficiency. The GWO can be applied to find the optimal settings for various process parameters, such as cutting speed, feeding rate, temperature, and pressure, in manufacturing processes like machining, welding, and injection moulding.

The paper (Jenarthanan & Ramesh, 2024) focuses on optimizing the process parameters of the Wire Electrical Discharge Machining (WEDM) using the Grey Wolf Optimizer (GWO). The study presents the GWO as an effective nature-inspired metaheuristic technique. It is applied to optimize the critical parameters in the WEDM, such as cutting speed and surface finish, leading to an enhanced machining performance. The results demonstrate that the GWO is a powerful tool for improving the efficiency and precision in the WEDM processes.

Recent research (Sooncharoen, Pongcharoen & Hicks, 2020) investigates the application of the Grey Wolf Optimizer (GWO) to production scheduling within the capital goods industry. The study focuses on optimizing complex production schedules, which is critical in the industries that produce high-value, customized goods. By using the GWO algorithm the authors demonstrate its ability to handle large-scale, and multi-stage scheduling problems effectively.

3. Algorithms' implementation, experimental tests and results analysis

3.1. Hardware structure of Flexible Manufacturing System

The manufacturing system used for the research is an educational system comprised of seven production stations. These stations are divided into assembly stations and stations dedicated to product disassembly. Additionally, a flexible cell is utilized, mounted at workstation three, which can produce a different type of product compared to the system's primary production output. (Figure 1a). The manufacturing system's architecture is linear, enabling the integration of multiple assembly flows due to the use of robotic systems in production. As a result, the system offers a high degree of flexibility for both assembly and disassembly processes. This system can assemble three types of products: standard products, multi-layer standard products, and multi-layer hybrid products, all through predefined production flows (Figure 1 b).

a)

b)

Figure 1. a) The flexible manufacturing system from ICSTM;
b) The product components used to produce the finished products in the manufacturing system

3.2. Architecture of energy monitoring system on FMS

The production system also integrates an intelligent energy consumption monitoring system. This system allows the acquisition of data related to energy consumption. The obtained data are recorded in tables and subsequently analysed to derive the mathematical models necessary for the optimization process. (Figure 2).

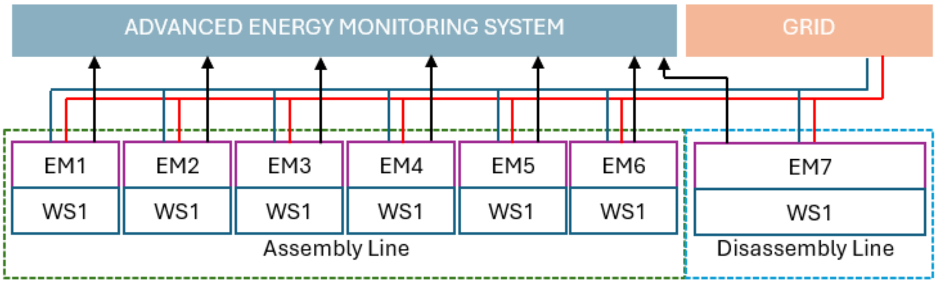


Figure 2. The general architecture of the energy consumption management system

In accordance with the manufacturing flow implemented on the production line, various production scenarios can be analysed. For the present research, the chosen production scenario involves the creation of a simple product. This scenario involves crossing the first five production stations in a sequential order to manufacture the product. This scenario can only be analysed using a mathematical model developed based on the consumption behaviour of each assembly station.

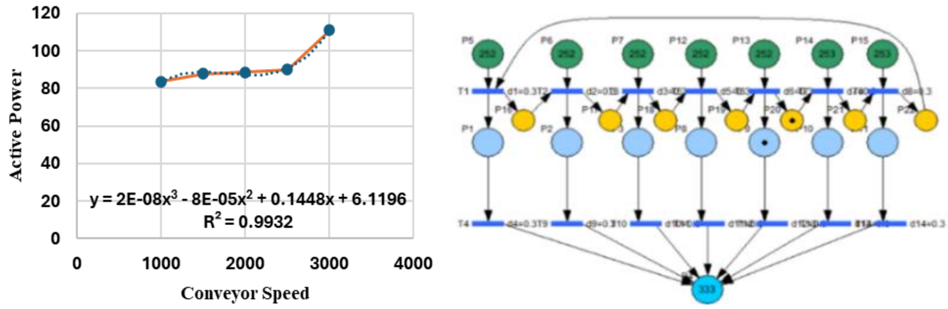
$$\vec{T}=\begin{pmatrix} (-1*10^{-07}*v_1^2-0.0004*v_1+8.0723)*(2*10^{-08}*v_1 3-8*10^{-05}v_1^2+0.1448*v_1+6.1196)+tsi_1*43.9193 \\ (-2*10^{-09}v_2^3+1*10^{-05}*v_2^2-0.0246*v_2+31.743)*(4*10^{-09}v_2^3-2*10^{-05}v_2^2+0.0264*v_2+9.6697)+tsi_2*98.39177 \\ (6*10^{-09}v_3^3-4*10^{-05}*v_3^2+0.0571*v_3-12.951)*(-1*10^{-08}v_3^3+7*10^{-05}v_3^2-0.0974*v_3+171.96)+tsi_3*178.834 \\ (4*10^{-09}v_4^3-2*10^{-05}*v_4^2+0.0396*v_4+169.37)*(4*10^{-09}v_4^3-2*10^{-05}v_4^2+0.0396*v_4+169.37)+tsi_4*131.9418 \\ (4*10^{-09}v_5^3-2*10^{-05}*v_5^2+0.0264*v_5+9.6697)*(-1*10^{-08}*v_5^3+5*10^{-05}*v_5^2-0.0775*v_5+74.103)+tsi_5*25.11458 \end{pmatrix} \quad (11)$$

where: v_1, v_2, v_3, v_4, v_5 are the equivalent speeds of the conveyors and $tsi_1, tsi_2, tsi_3, tsi_4, tsi_5$ are the delay times.

3.3. Data collection

For each workstation, smart meters were used to monitor the energy consumption in real time. The data collected were saved in CSV format. Subsequently, using Microsoft Excel, the consumption graphs were created, facilitating the development of the optimization function utilized within the algorithms. An example is presented in Figure 3a. The mathematical representation of the data acquisition process from the manufacturing system was modelled using Petri Nets (PN). From the modelling, the sequential nature of the queries made by the control system to the meters can be observed (Figure 3b).

After obtaining the data related to the energy consumption, a Machine Learning algorithm known as the polynomial regression was implemented to derive the mathematical model of the consumption in relation to the conveyor speed. This model was used to obtain the vector “T” (11). By summing up the elements of the vector T, the total energy consumption of the entire production system can be determined. Each element of the vector represents the energy consumption of an individual production station for the manufacturing flow of the standard product.



a) b)

Figure 3. a) The dependency of equivalent speed on active power for EM 1 obtained through polynomial regression; b) Petri Nets Model of the process of acquiring data from the meters

3.4. Synthetic analysis of algorithm implementation results

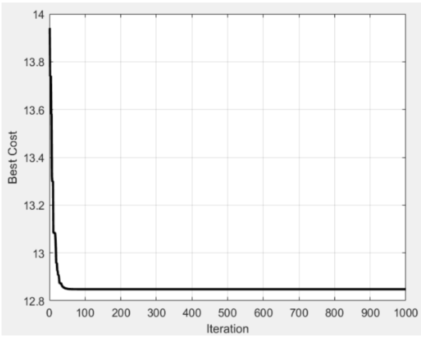
To optimize the production processes, it is essential to conduct experiments aimed at identifying the algorithm with the best optimization performance. Thus, the focus was on applying the single-objective algorithms. The purpose of applying these algorithms is to optimize the production process implemented on the FMS, while also identifying the potential improvements for the further development of the multi-objective algorithms. In this context, the present research was based on the premise of implementing the following algorithms: GA (Genetic Algorithm), PSO (Particle Swarm Optimization), ACO (Ant Colony Optimization), and GWO (Grey Wolf Optimization). To implement these algorithms, a mathematical model of energy consumption in relation to the speed of the transport systems integrated into the FML was developed based on the polynomial regression.

The Synthetic Analysis of the Algorithm Implementation Results is presented below:

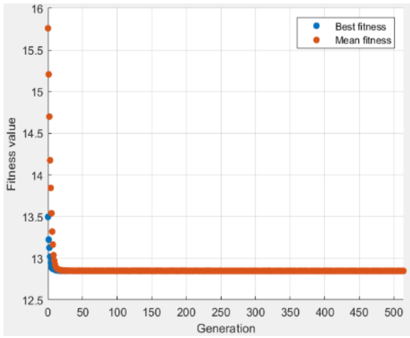
- the Ant Colony Optimization (ACO) algorithm was applied to the objective function identified through the polynomial regression. Figure 4a represents the convergence graph of the energy consumption towards the minimum value. The applied algorithm used the following parameters: five variables, with a lower bound of 1000 and an upper bound of 2000, a maximum of 1000 iterations, a population size of 40, an intensification factor of 0.5, and a deviation distance of 1. The minimum value identified was 12.847 W*h. This value was obtained for the following speed values: v1=1000, v2=1000, v3=2000, v4=1000, and v5=1000. The algorithm optimized these values in a time span of 0.703 seconds;
- the application of the genetic algorithm to the optimization function, presented in the *Data Collection* subsection, resulted in identifying the minimum energy consumption

of the production system. The optimization parameters for the algorithm are as follows: a maximum of 1000 generations, a tolerance of 0.000001, a population size of 200, 50 iterations before algorithm termination, and a crossover fraction of 0.8. The minimum identified value was 12.8479 W*h, obtained for the speed values v1=1000, v2=1000, v3=2000, v4=1000, and v5=1000. The algorithm completed the optimization in 21.994 seconds (Figure 4b);

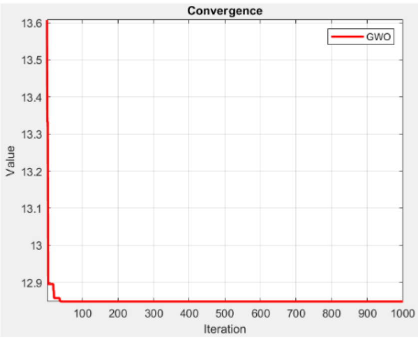
- the GWO algorithm, applied to the optimization function developed in the *Data Collection* subsection, achieves the optimal electrical energy consumption. To minimize the energy consumption, the following parameters were applied: 10 agents and a maximum of 500 iterations. The obtained value was 12.847 W*s, corresponding to the speed values of v1=1000, v2=1000, v3=2000, v4=1000, and v5=1000. The algorithm completed the optimization in 0.058 seconds (Figure 4c);
- the PSO algorithm, applied to the optimization function obtained through the polynomial regression (PR), achieves a minimum energy consumption of 12.847 W*s. This value corresponds to the speed values: v1=1000, v2=1000, v3=2000, v4=1000, and v5=1000. The optimization time of the algorithm is 0.543 seconds (Figure 4d).



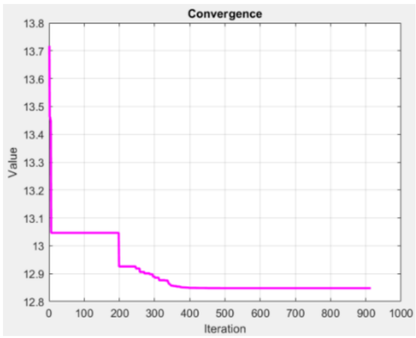
a)



b)



c)



d)

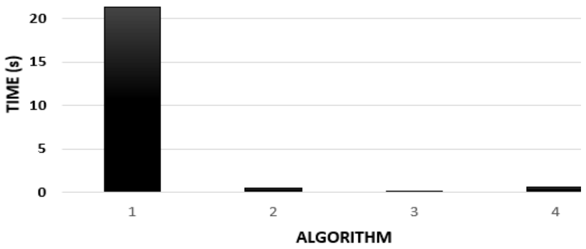
Figure 4. The graphical representation of energy consumption convergence of the algorithms: a) ACO; b) GA; c) GWO; d) PSO

4. Comparison of the results

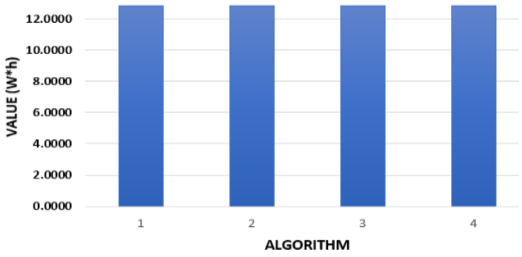
The energy optimization of the Flexible Manufacturing Line (FML) refers to the implementation of measures aimed at reducing the energy consumption of the production line by adjusting the equivalent speed of the workstations. The single-objective optimization focused on the assembly flow of a standard product, which involves passing through the following workstations: WS1, WS2, WS3, WS4, WS5, and WS6. This process considers both the assembly time and delay time to determine the energy consumption.

The comparative analysis of the implementation of energy consumption optimization algorithms highlights the following aspects:

1. the algorithms applied to the mathematical model iteratively optimize the equivalent speed parameters. The runtime of the algorithms varies depending on the method used to identify the minimum value of the objective function. Figure 5a illustrates the runtime of each algorithm. It can be observed that the GWO algorithm offers the best results in terms of execution time;
2. the analysis of the algorithms from the perspective of identified as the minimum energy consumption. As shown in the chart in Figure 5b, the minimum value was obtained using each implemented algorithm. However, from an efficiency standpoint, the GWO algorithm is significantly more effective, due to its reduced processing time, in identifying the minimum value;
3. in addition, to assess quality, the graphical representation of the working speeds for each workstation identified by the applied algorithms was considered (Figure 6a). These speeds show no variation, due to both the computational performance of the algorithms and their high compatibility with the problem being solved. Considering that the most efficient algorithm in terms of the minimum value identified is the GWO, the equivalent speeds determined by this algorithm can be implemented on the production line to achieve the optimal electrical energy consumption performance;
4. the identification of the delay times at the workstations corresponding to the speeds determined by the optimization techniques. The identified delay times are graphically represented in Figure 6b;
5. the optimization time has critical implications when the real-time process optimization is required. Consequently, the shorter the execution time, the more effectively the implemented algorithms can dynamically adapt the conveyor speeds to the production conditions.

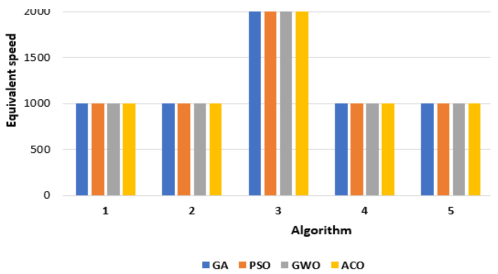


a)

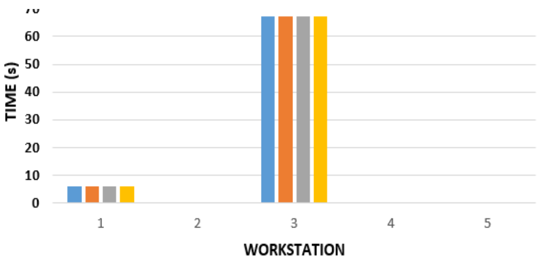


b)

Figure 5. Graphical representation of a) the working time; b) the minimum energy consumption for each algorithm used: 1 - GA (Genetic Algorithm), 2 - PSO (Particle Swarm Optimization), 3 - GWO (Gray Wolf Optimization), and 4 - ACO (Ant Colony Optimization)



a)



b)

Figure 6. a) The equivalent speed; b) Delay time values associated with each station for each algorithm used: GA (Genetic Algorithm), PSO (Particle Swarm Optimization), GWO (Gray Wolf Optimization), and ACO (Ant Colony Optimization)

5. Conclusions

This paper presents the research in the field of the single-objective optimization used to enhance and optimize the manufacturing processes implemented on the FML. The current research contributes significantly to the efficiency of the production processes through the implementation of advanced algorithms. The study considered various methods for collecting datasets related to the energy consumption on the production line within the manufacturing processes implemented on the FML: energy consumption, operational parameters of the system, production times, and delay times. In addition to these, the Machine Learning algorithms were applied to the datasets analysed to identify the mathematical models that describe the dynamics of the relationships between variables, specifically considering the working speed in relation to the system's energy consumption.

The contribution focused on the method of data collection through an advanced data acquisition system related to the energy consumption. This facilitated a better understanding of the dynamics of the energy consumption as well as the dynamics of the processes implemented on the FML through the mathematical models obtained. Based on the mathematical models, the single-objective optimization algorithms, such as GA (Genetic Algorithm), PSO (Particle Swarm Optimization), ACO (Ant Colony Optimization), and GWO (Gray Wolf Optimization) were applied to determine the optimal conveyor speeds for the manufacturing system. This allowed for the identification of speeds at which the manufacturing system consumes the minimum amount of electrical energy, thereby maximizing the energy efficiency.

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