Results in Engineering 25 (2025) 104262

Contents lists available at ScienceDirect

Results in Engineering

journal homepage: www.sciencedirect.com/journal/results-in-engineering

ANFIS-optimized control for resilient and efficient supply chain performance in smart manufacturing

Mona A. AbouElaz [a], Bilal Naji Alhasnawi [b], Bishoy E. Sedhom [c], Vladimír Bureš [d,*]

[a] Mansoura University, Faculty of Engineering, Production Engineering and Mechanical Design Department, Mansoura 35516, Egypt
[b] Department of Computer Technical Engineering, College of Information Technology, Imam Ja'afar Al-Sadiq University, Al-Muthanna 66002, Iraq
[c] Mansoura University, Faculty of Engineering, Electrical Engineering Department, Mansoura 35516, Egypt
[d] Faculty of Informatics and Management, University of Hradec Kralove, Hradec Kralove 50003, Czech Republic

ARTICLE INFO

Keywords:
Smart manufacturing
Cyber-physical systems
Operational cost
Operation control
Adaptive neuro-fuzzy inference system
Butterfly optimization algorithm

ABSTRACT

Due to the dramatic revolution in global trade, competition, and the epidemic of COVID-19, the Small and Medium Enterprises (SME's) production paradigm has been evolving and gaining traction to meet its dynamic demands and challenges for industrial process adaptability and standards. As a result, they develop Cyber-Physical Production Systems (CPPS) by integrating CPS modules into their manufacturing processes. This integration is founded on the belief that value-added services result from technological advancements. Better tools would be needed in the future to provide process management, monitoring, and maintenance. Our main goal is to support existing SMEs with an economically adaptable solution for technological improvement. So, to make the proposed solution sustainable, the whole process must be analyzed, from the input of raw materials to the output of finished products. This paper evaluates the supply chain (SC) using the adaptive neuro-fuzzy inference system (ANFIS) classification control algorithm to improve the SC performance, maximize the system quality, and minimize the cost. Also, the butterfly optimization algorithm (BOA) is proposed for obtaining optimal parameters for the ANFIS controller algorithm. The performance of the SC is evaluated on the real-time production system, and the results are analyzed to prove the effectiveness of the proposed algorithm. The proposed algorithm can be applied to CPS components in the current SME environment to improve the performance of manufacturing processes.

1. Introduction

Cyber-Physical Production Systems (CPPS) are at the forefront of Industry 4.0, embodying the integration of computational intelligence with physical processes to revolutionize manufacturing through real-time data exchange, process optimization, and automated decision-making [1]. These systems significantly enhance production efficiency, scalability, and adaptability while addressing critical challenges such as cybersecurity, interoperability, and system reliability [2,3]. CPPS also drive the transition from automated to autonomous manufacturing systems, leveraging artificial intelligence (AI), Internet of Things (IoT) technologies, and digital twin frameworks to achieve higher levels of precision and responsiveness [4,5]. All these digital and smart factory features are based on the data generated by the interconnection of large numbers of autonomous systems in a factory [6–8]. By combining IoT technology and CPS [9], cyber-physical manufacturing services (CPMS) implement service-oriented smart manufacturing systems. The CPMS scope refers to the supply chain's factory processing units and logistic components [8]. Also, Mingwei Lin et al. [10] evaluate the performance of the IoT platforms using an integrated probabilistic linguistic multicriteria decision-making method. Despite these advancements, the adoption of CPPS by Small and Medium Enterprises (SMEs) remains constrained by high costs, technological complexity, and limited access to scalable solutions [11]. To overcome these barriers, this study introduces an innovative framework integrating the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Butterfly Optimization Algorithm (BOA). ANFIS combines fuzzy logic and artificial neural networks to facilitate intelligent, adaptive control [12], while BOA enhances ANFIS by optimizing parameters for greater accuracy and performance [13,14]. The integration of IoT-enabled sensors enables the collection and analysis of real-time data, empowering SMEs with actionable insights to streamline operations and reduce costs [15].

* Corresponding author.
E-mail addresses: maboueleaz@mans.edu.eg (M.A. AbouElaz), vladimir.bures@uhk.cz (V. Bureš).

https://doi.org/10.1016/j.rineng.2025.104262
Received 16 September 2024; Received in revised form 15 January 2025; Accepted 3 February 2025
Available online 4 February 2025

The objectives of this research are to improve supply chain (SC) performance by enhancing productivity, reducing operational costs, and maximizing system quality. The proposed framework was rigorously tested in a real-time smart manufacturing environment, demonstrating notable advancements in inventory management, capacity utilization, and financial performance [16]. Additionally, the framework addresses core challenges such as real-time decision-making, scalability, and the effective utilization of data-driven optimization techniques [17].

This research highlights the transformative potential of CPPS to foster sustainability and resilience in manufacturing systems. By enabling SMEs to integrate advanced technologies, this study bridges the gap between traditional and digital manufacturing, ensuring that these enterprises remain competitive in increasingly data-driven markets [18]. Furthermore, the findings emphasize the importance of distributed systems, IoT, and digital twins in creating adaptable and secure manufacturing ecosystems [19].

1.1. Related work

In literature, production systems have historically faced challenges such as low efficiency and ineffective responses. These issues were primarily attributed to the lack of transparency and delays in manufacturing operations. However, with advancements in information and communication technologies, the production model has evolved from mass production to mass individualization. Consequently, the corresponding production system has undergone a transformation from automated to autonomous, enabling more efficient and responsive operations [6]. Lozano and Vijayan [8] examined existing literature about CPS from 2006 to 2018 in the engineering bibliographic database published by Elsevier “Compendex”. The main findings defined CPS as a closely integrated, diversified, large-scale network with complex multiple time scales. They also summarized the CPS design challenges of developing, modifying, integrating abstractions, and predicting timing opening time and physical interconnection of physical devices. Furthermore, security is a critical issue in CPS. Enzo Frazzon et al. [18] proposed and implemented a data-driven adaptive planning and control approach based on simulation-based optimization to determine the most suitable dispatching rules in real-time under varying conditions. The author’s work has been tested in a Brazilian manufacturer of mechanical components for the automotive industry. The results show that the proposed approach proved better operational performance than the company’s previous procedure than static dispatching rules.

Ding et al. [16] build the interconnection and interoperability of a physical shop floor and corresponding cybershop floor using the CPS and digital twin technologies. Authors expected DT-CPPS to be considered a reference model for shop floors through system transformation into smart manufacturing. Lee et al. [17] proposed a blockchain architecture consisting of a unified three-level considered reference model for researchers and industries. It mitigated the CPS concerns related to inherent real-time implementation in the manufacturing application domain. That proposed model ensured the operation of safe and reliable manufacturing systems, including communication and data flow inside the existing CPPS structure. Francisco and Luiz [20] presented a supportive approach to SC performance evaluation composed of the SCOR metrics and adaptive network-based fuzzy inference system (ANFIS). Through these studies, 56 candidate topologies were implemented and assessed using MATLAB. That study’s main contribution was the proof of prediction accuracy learning ability to the proposed approach based on historical data. Also, they proved the suitability to support decision-making under uncertainty and better results interpretability. Bayhan et al. [21] proposed a universal production supply concept. The proposed concept focused on a decentralized, controlled supply. This work has been implemented with several cyber-physical system entities, which software agents represented. This study includes a key performance indicator system that assesses efficiency, and the author called it process status indicators. The proposed indicator system results stated that the proposed concept is more efficient than the Kanban supply. Fink et al. [22] displayed optimization for manual assembly using a dynamic value stream in the learning factory for cyber-physical production systems. They proved that the learning factory of cyber-physical production systems could minimize the gap of digital competency for teaching the recent technologies, such as the selection and usage of digital assistance systems. For instance, they found that they could increase the overall outcome of products to 15 percent with the aid of digital assistance systems.

Lin et al. [23] proposed a problem-solving approach for evaluating startup companies based on a hesitant fuzzy linguistic decision-making method. The study introduces a comparison method based on the experts’ psychology, and the ratio of score value to deviation degree is proposed to compare the hesitant fuzzy linguistic term sets. Yang et al. [24] discussed the reasons and approaches to adopting manufacturing firms’ digital technologies and their impact on supply chains. The authors reviewed and analyzed the literature; then, they highlighted the main finding identifying the main drivers of manufacturing firms adopting digital technologies. Secondly, it proposed an adoption model of the process. Thirdly, they evaluate the impact of the adoption on supply chains into four aspects: SC efficiency, SC structure, sustainability, and innovation.

Neto et al. [25] introduced a demonstrated case study for the digital twin operationalization which might support the management of manufacturing flexibility, after the implementation of mix modifications on cost, speed, and dependability. The suggested approaches provide support to managers and aim to enhance consistency in the speed of delivery and the quality of decision support. By utilizing digital twin procedures, managers can benefit from a reliable and systematic service workflow, as well as the prompt delivery of decision support services that operate in near real-time. Although the digital twin concept and the supported technologies depend on the reviewing and adaptation process for both training and management processes. So, the authors highlighted one of the digital twin implementation challenges which was the availability of the highly skilled workforce and their expertise in using such technologies. Fuzzy logic is applied in many other systems to enhance its performance. Chao Huang et al. [26] introduce novel distance measures and score functions for Pythagorean fuzzy sets for evaluating solid-state disk production and energy projects. Mingwei Lin et al. [27] propose a new technique for order of preference by similarity to ideal solution (TOPSIS) for the linguistic Pythagorean fuzzy sets dependent on correlation coefficient and entropy measure. It is applied for selecting firewall productions and evaluating computer systems’ security. Mingwei Lin et al. [28] enhance the traditional TODIM using the hesitant fuzzy linguistic term sets. It is applied for the evaluation and ranking of several satellite launching centers. Mingwei Lin et al. [29] improve the performance of the Pythagorean fuzzy sets using the directional correlation coefficient to estimate the relation between two Pythagorean fuzzy sets by considering four parameters of the Pythagorean fuzzy sets. Bamakan et al. [30] Proposed a distributed and trustworthy framework for the Service Supply Chain under the condition of uncertainty. The proposed framework evaluated the performance of the service SC through a smart and self-learning hierarchical evaluation system enabled by integrating blockchain, IoT, and big data named “Di-ANFIS.”.

The Butterfly Optimization Algorithm (BOA) has emerged as a promising bio-inspired metaheuristic optimization technique, widely recognized for its simplicity and effectiveness. Despite its growing popularity, there is still considerable potential for further exploration in parameter optimization. Numerous studies have demonstrated its success across diverse domains, including engineering design, power systems, and machine learning. For instance, Tiwari et al. enhanced BOA by introducing an improved binary variant combined with Adaptive β-Hill Climbing. This innovative approach significantly improved feature selection and classification accuracy while effectively reducing computational complexity in data analysis tasks [31].Similarly, Gonzalez-Sanchez et al. developed a multi-objective BOA for protein encoding, optimizing key parameters such as codon adaptation, Hamming distance, and GC content, thereby advancing applications in bioinformatics [32].Wang et al. proposed a hybrid model integrating BOA with variational mode decomposition and long short-term memory networks, achieving notable gains in short-term wind power prediction accuracy [33].

El-Hasnony et al. introduced a hybrid optimization model, BOAPSO, by integrating BOA with Particle Swarm Optimization (PSO) to enhance feature selection. The hybrid model aimed to boost classification accuracy, reduce the number of selected features, and improve computational efficiency. Evaluations using 25 UCI datasets and a COVID-19 dataset demonstrated BOAPSO's superior performance compared to PSO, BOA, and GWO, establishing it as a more efficient alternative for large-scale data classification tasks [34]. Prasanthi et al. presented a Quantum Chaotic Butterfly Optimization Algorithm, incorporating chaos theory and quantum computing concepts. The algorithm introduced a ranking-based strategy to balance exploration and exploitation, addressing the limitations of conventional BOA. Extensive tests on benchmark functions and real-world optimization problems, including photovoltaic system parameter extraction, highlighted QCBOA's enhanced convergence speed and precision compared to BOA, PSO, and DE [35]. Abaci et al. proposed a Modified Effective Butterfly Optimizer (MEBO) designed for solving the Optimal Power Flow (OPF) problem. This algorithm featured advanced penalty mechanisms for robust constraint handling, ensuring feasible solutions while optimizing multiple objectives such as fuel cost, emissions, and voltage deviation. Comparative evaluations on IEEE 30-bus and 57-bus systems demonstrated MEBO's superior performance in managing renewable energy integration and reducing operational costs [35].

Although significant advancements have been made in the domains of CPPS, adaptive optimization algorithms, and their applications in smart manufacturing, the literature highlights several key areas that require further exploration:

- Existing studies focus heavily on large-scale industries, with limited attention given to affordable and adaptable solutions for Small and Medium Enterprises (SMEs).
- There is a lack of research demonstrating real-time application of advanced control algorithms like ANFIS integrated with optimization techniques in smart manufacturing environments.
- The role of IoT in enhancing supply chain performance has not been fully utilized to create a cost-effective and high-quality manufacturing process.
- Challenges such as security, scalability, and real-time decision-making in IIoT-based systems remain inadequately addressed.
- Few studies explore hybrid optimization models that combine robustness and flexibility to handle dynamic and complex supply chain environments.

1.2. Contributions and paper organization

In this paper, a smart manufacturing process has been proposed. The ANFIS classification algorithm has been implemented to evaluate the performance of the supply chain. The BOA approach has been applied to obtain the optimal parameters of the ANFIS controller algorithm. The ANFIS control strategy is based on fuzzy logic (FL) and the artificial neural network (ANN). It depends on five operational and training layers to obtain the optimal solution for the classification process. These layers are the transformation, rule base, normalization, consequent, and summation layers. The main objectives of this study are to enhance the SC performance, maximize the system quality of service, and reduce the resultant total cost. IoT has been used to communicate between the different agents in the manufacturing process. A real-time CPPS has been used to prove the effectiveness of the proposed control method. The results show the proposed method's ability to be applied to CPPS components in the current SME environment to improve the performance of manufacturing processes.

The main contribution of this paper can be summarized as follows.

1- Proposing the integration of ANFIS and the BOA to establish a novel and efficient optimization framework for supply chain performance in smart manufacturing.
2- Designing and validating a real-time framework within a CPPS, showcasing its practical effectiveness and scalability in dynamic industrial environments.
3- Investigating the impact of the proposed approach on supply chain metrics, demonstrating significant improvements in system efficiency, cost reduction, and product quality through optimized decision-making.
4- Enhancing system interoperability by leveraging IoT technologies for seamless communication, real-time monitoring, and adaptive control within the smart manufacturing ecosystem.
5- Developing a cost-effective and adaptable framework tailored to meet the operational and financial requirements of SMEs.

The paper is organized as follows: Section 2 represents the proposed smart manufacturing system, Section 3 introduces the proposed ANFIS control method based on BOA and describes the proposed production control method for smart manufacturing, Section 4 presents the case study and results discussion and analysis. Finally, Section 5 concludes the paper.

2. Proposed smart manufacture

The proposed framework can evaluate the organization's performance and give feedback to organization management to set and decide the required improvement actions to meet its strategic goals. The proposed framework consists of three phases. The role of information in a manufacturing company can be simply summarized in Fig. 1. The figure provides a visual representation of the critical interdependencies in a supply chain. It highlights how the three flows (materials, information, and money) are interlinked and constrained by one another. Material flow (solid arrows) is constrained by payment receipt (money flow, dashed arrows), while production and delivery depend on order and documentation information (information flow, dotted arrows). Key takeaways include:

- **Interdependence**: None of the flows operates in isolation. Each depends on the other for efficient functioning.
  - Example: Materials can only move after the relevant information (e.g., order confirmation) and payment are processed.
- **Sequential Processes**: The figure likely conveys the sequential nature of SC processes (e.g., materials flow only after order information is received).
- **Control Points**: The constraints act as control points to ensure that each step aligns with operational goals, minimizing wastage or errors.

Considering the critical supply chain flows including Material and information through the manufacturing system. one can immediately point out the specific importance of information:

1- Material flow constrains money flow (no payment until delivery)
2- Information flow constraints
  - Material flow (no delivery until shipment documentation is issued)
  - Money flow (no payment until invoice is issued)

First, it starts with defining and listing the visual representation of the organization's SC activities. Quality management tools are essential as they help visualize the scope, barriers, and improvement opportunities for the organization's top management to plan and decide

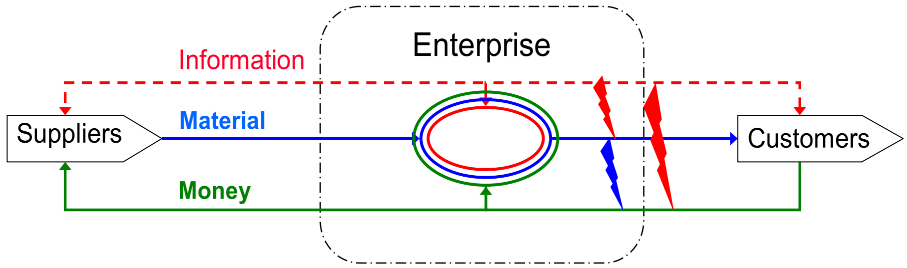


Fig. 1. Interconnection of material, information, and money flows in a smart manufacturing SC.

appropriately. These tools are the SIPOC diagram, flow charts, and the SIPOC. We start to collect the required data by tracking the processes' workflow with visual representation with the help of factory documents. The top SIPOC is represented in Fig. 2. The second step is to assess the organization's performance using the proposed multicriteria performance evaluation framework. One of the crucial success factor in maximized the supply chain's potential is to develop the suitable performance evaluation indicators to optimize the supply chain effectiveness and efficiency.

After collecting the SC KPI of processes, it will be entered into system software and displayed in the previous forms as a flowchart. This visual display of data will point out the unnecessary, not value-added process, activity, motion, waiting time through SC activities, especially for paperwork flow and its actual time consumed. It will also support management to focus and extract the improvement initiatives in every SC activity. The performance evaluation of a SC is necessary as it helps motivate employees and provides essential feedback to focus on weak areas. It measures the degree to which the firm has achieved its strategic goals. Briefly, the different elements and links comprising an SC need to be evaluated for its performance to monitor and control the process/es effectively. The selected performance indicators asses the SC practices effectiveness through the supply chain mainly four sectors supplier, production, inventory, and employee & learning growth. The supplier's performance was assessed through supplier lead time, technical competence, delivery reliability, and supplier agility. At the same time, production performance indicators have been chosen as productivity, range of products and services, capacity utilization, cycle time, the effectiveness of scheduling techniques, total supply-chain cycle time, and flexibility/adaptability. Also, inventory performance indicators are inventory turn, inventory level, absolute inventory, storage quality, warehouse cost, and warehouse utilization. The performance indicators of employee & learning growth performance are employee absenteeism index, employee satisfaction level, percentage of employees trained, and employee retention index. Through assessing customer relationship performance, certain metrics have been used such as, customer satisfaction index, order fill rate, and on-time delivery. Also, financial performance indicators are total cost, financial productivity, cost as a percentage of sales, and return on investment ROI. The evaluation metrics were calculated according to the following definitions:

Scheduling Effectiveness: assessing the Scheduling activity refers to the time or date are undertaken. This indicator determines the effectiveness of production resources flow through the production system. It can be calculated as follows.

$$Effect.\ per = \frac{Production\ Quantity}{Planned\ Rate} * 100 \tag{1}$$

Production productivity: this indicator assesses the efficiency and effectiveness of the manufactured products that have been delivered to its intended destination.

Inventory Level: Measures the desired stock in hand; according to the plant contracts, it was about 15 days.

Capacity Utilization: this indicator assesses the percentage utilization of the machine. The importance of this indicator directly affects the speed of response to customers' demands. It can be calculated as follows.

$$Capacity\ utilization = \frac{Actual\ Capicity}{Full\ Capicity} \tag{2}$$

Total order cycle time: It can be calculated as the total time starts by order entry time passing by all the required activities such as order planning time, order sourcing, assembly, until finished goods have been delivered.

Total supply-chain cycle time: It can be calculated as the sum of order lead time and the wasted time in supply chain activities.

Percentage of employees Trained: It can be calculated as the percentage of employees estimates it participated in at least one training program during the examined year.

Employee commitment Index: this indicator reflects the degree of attraction of work environment's and the workforce's commitment toward organization targets. It can be calculated as the percentage of number of absence days to the total working days per year.

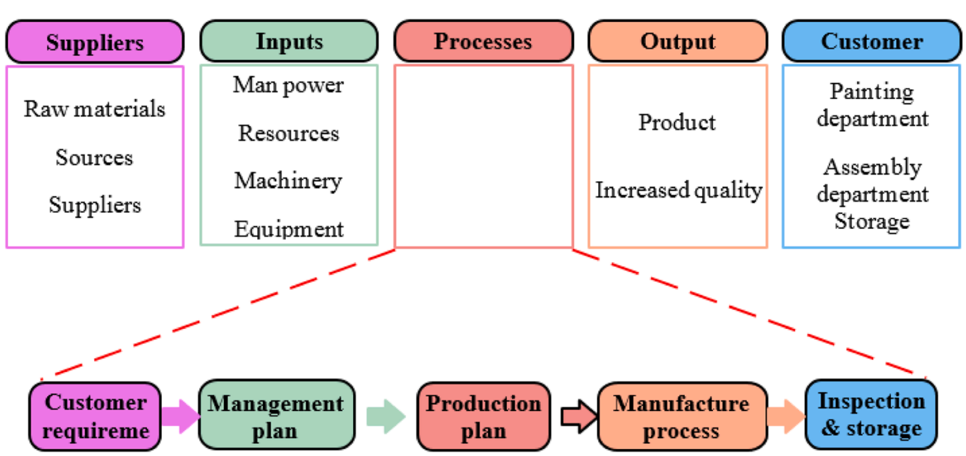


Fig. 2. SIPOC block diagram.

Financial Productivity: It can be calculated as the sum of the financial inputs such as total investment such as salary, overheads, utility, etc. divided by the total revenue such as sales income.

Order fill Rate: It can be calculated as the ratio of the orders fulfilled and received.

Return on investments (ROI): this indicator assessed the percentage of real cash return on the capital invested. It can be calculated as dividing the net income by the invested capital.

Customer satisfaction Index: It can be assessed through making a structured survey and the survey results analysis applied through customer judgments on detailed dimensions using the weighted sum.

The third step is applying the proposed architecture of the smart manufacture based on using a multi-agent system to enhance the monitoring and controlling of each operational process in the SC system. The proposed method has been applied optimally to improve the SC process using the ANFIS controller. Also, IoT technology has been used to provide appropriate monitoring and data collection among all agents in smart manufacturing. Fig. 3 illustrates the main structure of smart manufacturing based on the IoT platform-as-a-service. The IoT platform comprises five layers: the SC appliances layer, network layer, data processing layer, control system layer, and IoT service layer. The first layer includes all SC appliances that perform smart manufacturing, inventory, material handling, production processes, and quality inspection. It ensures seamless integration of devices and machinery in smart factory environments to optimize operations. The second layer establishes communication protocols between connected appliances in smart manufacturing, enabling efficient data exchange through technologies such as Wi-Fi, Bluetooth, and 5G.

The third layer is responsible for collecting and processing information and data within the IoT platform structure. This layer utilizes edge computing and cloud-based services to analyze data in real time, facilitating actionable insights. The fourth layer applies to the proposed control method for smart manufacturing performance evaluation and improvement. This layer integrates advanced controllers, such as the ANFIS controller, to enhance system performance and ensure optimal decision-making processes.

The IoT service layer, the fifth layer, comprises the information and data storage memory. Data analysis is performed in this layer to optimize the use of SC appliance data. Furthermore, this layer enables predictive analytics to forecast future SC demands and trends, leveraging machine learning algorithms and big data analytics. The platform also integrates real-time monitoring capabilities through interconnected sensors and devices, ensuring proactive maintenance and reducing downtime. These advancements enhance the responsiveness and flexibility of the SC, making it more adaptive to dynamic market conditions. The IoT platform structure, illustrated in the figure, highlights the interconnectivity and role of each layer in achieving a smart, efficient, and resilient supply chain.

3. Proposed production control method for smart manufacturing

This section presents the proposed control method of SC production as follows. To address the challenges of smart manufacturing, we propose a novel production control method that combines the strengths of ANFIS and IoT technologies. The core principles underlying our method are as follows:

- Real-time Data Acquisition: Leveraging IoT sensors, real-time data on various manufacturing parameters (e.g., machine status, product quality, energy consumption) is collected and transmitted to the control system.
- Data Preprocessing and Feature Extraction: Collected data is preprocessed to handle noise, outliers, and missing values. Relevant features are extracted to capture the underlying patterns and trends.
- ANFIS Model Development and Training: An ANFIS model is developed to approximate the complex nonlinear relationship between input variables (e.g., real-time data) and output variables (e.g., optimal control actions). The model is trained using a hybrid learning algorithm, combining gradient descent and least-squares methods to optimize the membership functions and rule base.
- Adaptive Control: The ANFIS model is continuously updated based on new data and feedback signals to adapt to changing conditions and improve control performance.
- Decision-Making and Control Actions: The trained ANFIS model generates optimal control decisions (e.g., adjusting machine parameters, scheduling production) to optimize the manufacturing process.
- IoT Integration: The control decisions are transmitted to IoT-enabled devices (e.g., actuators, robots) to execute the necessary actions and control the manufacturing process.

3.1. ANFIS control method based on butterfly optimization algorithm (BOA)

The proposed control method for the SC production processes is based on the ANFIS controller. The ANFIS control method is a hybrid technique that includes fuzzy logic (FL) and the artificial neural network (ANN). The operational process of the proposed controller is based on using the ANN for training the preparation of the input for FL, and then the output feedback of the ANN is used for FL adaptation. The ANFIS controller includes five layers to obtain the optimal output solution of the classification process. These layers are the transformation, rule base, normalization, consequent, and summation layers. Fig. 4 shows the structural diagram of the ANFIS classification method. x_1 and x_2 are the inputs to the ANFIS controller, whereas y is the controller's output. The number of inputs and outputs of the ANFIS controller is determined by applying an appropriate training model for the dataset. The dataset for

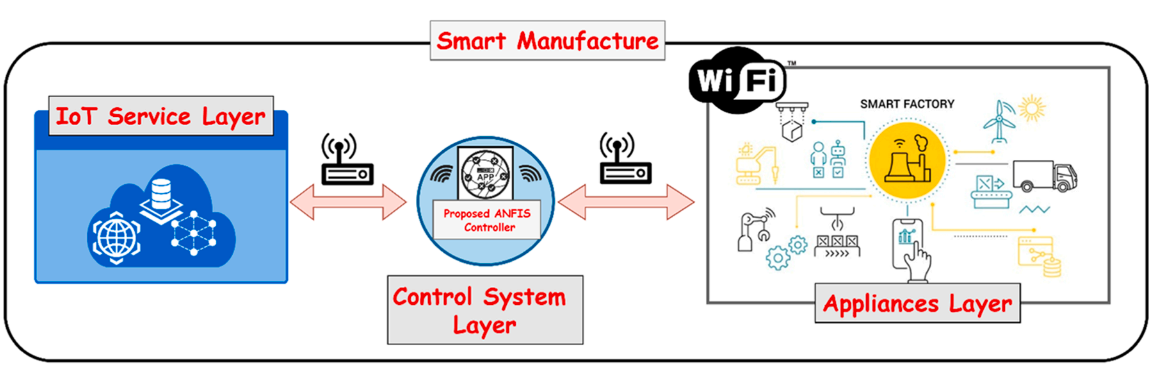


Fig. 3. Structure of the smart manufacture based on the IoT platform-as-a-service.

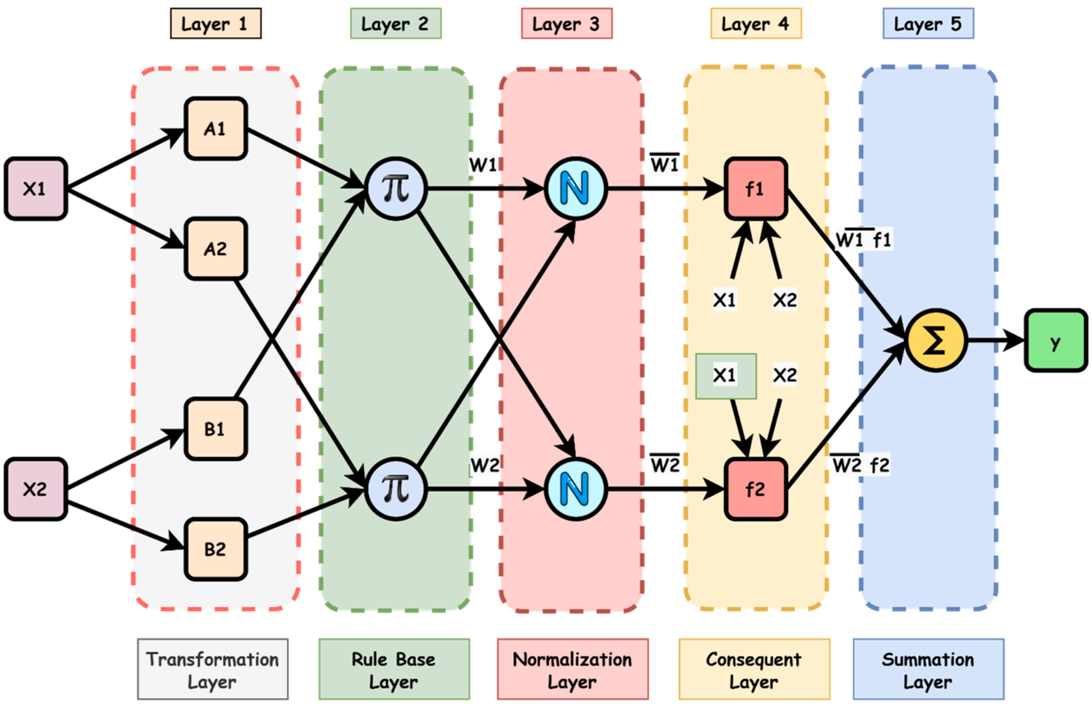


Fig. 4. Structure of ANFIS control layers.

the ANFIS training must be recognized, clustered in sections, and uniform. The fuzzy interface system (FIS) is developed using the dataset training method. The main objective of the ANFIS dataset training is the determination of the membership functions (MFs) of the ANFIS layers concerning the error criterion. The proposed ANFIS controller structure includes four MFs and four rules to obtain an optimal classification of the controller inputs. The function of each layer has been presented in the following subsections.

Sugeno-type FIS has been applied to formalize a systematic approach to perform if-then rules depending on the relationship between the inputs and the outputs. Two rules are formulated for the first-order Sugeno FIS that can be represented as follows [36];

$$Rule\ 1:\ If\ x_1\ is\ A_1\ and\ x_2\ is\ B_1;then\ y=\ p_1x_1+q_1x_2+r_1$$

$$Rule\ 2:\ If\ x_1\ is\ A_2\ and\ x_2\ is\ B_2;then\ y=\ p_2x_1+q_2x_2+r_2$$

where, p_1, q_1, r_1, p_2, q_2, and r_2 are linear parameters, and A_1, B_1, A_2, and B_2 are nonlinear parameters.

The transformation layer is the layer in which the crisp input values are transformed to fuzzy values suitable for the FIS. The equation that represents the fuzzy transformation process is as follows [37];

$$O_i^1 = \mu A_i(x_i) \quad for\ i = 1,\ 2 \tag{3}$$

where x_i is the i^{th} layer input, O_i is the grade of the membership of the layer inputs x_i is the fuzzy dataset A_i.

The rule base layer is a set of fixed nodes, including fixed rules, in which the output from this layer is the multiplication of all fuzzy input values resulting from the first layer. The results from the product of the fuzzy membership values are represented as firing strengths (FS). The equation describes this layer is as follows [37];

$$O_i^2 = \omega_i = \mu A_i(x_1).\ \mu B_i(x_2) \quad for\ i = 1,\ 2 \tag{4}$$

where x_1 and x_2 are the two-layer inputs, A_i and B_i are the fuzzy datasets.

The normalization layer evaluates the normalized FS concerning each rule. The normalized value is the ratio between the FS of the i^{th} rule belonging to the sum of all FS that is the output of the previous layer. The equation that represents the normalization process can be written as follows [37];

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\sum_{j=1}^{n}\omega_j} \quad for\ i,\ j\ \in \{1, \dots,\ n\} \tag{5}$$

where $\overline{\omega_i}$ is the output of the normalization layer, n is the number of the FS of the rule base layer.

The consequent layer is the defuzzification layer, in which the rule's weighted values are evaluated using the first-order polynomial. The calculation of the weighted values for the layer can be represented as follows [38];

$$O_i^4 = \overline{\omega_i}\, f_i = \overline{\omega_i}\ (p_ix_1 + q_ix_2 + r_i) \tag{6}$$

where $\{p_i,\ q_i,\ r_i\}$ are the parameters set of the first polynomial equation called consequent parameters.

The summation layer represents the output of the ANFIS controller in which the output obtained for each rule in the consequent layer are summed to form the controller output. The following equation represents the summation process [37].

$$O_i^5 = \sum_{j=1}^{n} \overline{\omega_i}\, f_i = \frac{\sum_{j=1}^{n}\omega_i\, f_i}{\sum_{j=1}^{n}\omega_i} \tag{7}$$

The training algorithm is applied to optimally obtain the parameters required for the ANFIS controller based on the butterfly optimization algorithm (BOA). BOA is considered a nature-inspired metaheuristic algorithm is emulating the butterfly food-searching mechanism [14]. In this optimization algorithm, butterflies utilize their smell sense to indicate the location of their fragrance (f). The BOA has three stages for butterfly foraging: initialization, iteration, and final stages [14]. Firstly, the controlling parameters of the BOA and the system objective function are handled. Secondly, the population of the BOA is defined based on the boundaries of the system parameters, and the fitness function of all butterflies is evaluated. Finally, the final solution is obtained using an iterative method.

The fitness function is calculated using all butterflies in different positions in the search space. The fragrance is generated based on the intensity of the stimulus (I) as follows [39];

$$f = cI^{a} \tag{8}$$

where c is the fragrance sensory, a is the power exponent, and f is the magnitude of the fragrance; c and a are in the range of $[0, 1]$ where c is the convergence speed while a is the algorithm control.

BOA has two search methods that can be applied; global and local search algorithms. Using the global search algorithm, the butterflies update their position in the search space toward the global best solution as follows [39];

$$x_i^{k+1} = x_i^k + f_i\left(u^2 g^* - x_i^k\right) \tag{9}$$

where, x_i^k is the i^{th} butterfly for the iteration k, g^* is the global best solution, f_i is the fragrance of the i^{th} butterfly, and u is the random number in a range between $[0, 1]$.

The local search algorithm can be represented as follows [39];

$$x_i^{k+1} = x_i^k + f_i\left(u^2 x_j^k - x_v^k\right) \tag{10}$$

where, x_j^k and x_v^k are the j^{th} and v^{th} butterflies for the iteration k in the search space.

The optimal solution is reached concerning the stopping criteria such as the maximum iteration number or the minimum error tolerance obtained.

3.2. Proposed production control methodology

In this paper, the smart manufacturer's SC performance is enhanced using an ANFIS control method. The main objectives are to improve financial profit, SC performance, and system quality. Firstly, the data is collected and measured through IoT-based sensors from all the system equipment. These data are sent to the control center using a communication channel-based Wi-Fi, then the data are analyzed and processed using the IoT platform. The proposed control method ensures the optimal production schedule to improve the performance of the SC. The proposed production control method can be shown in the flowchart in Fig. 5. The proposed method involves the following steps:

1. Data Collection and Preprocessing: Collect real-time data from IoT sensors and clean and preprocess the data to remove noise and outliers.
2. Feature Extraction: Extract relevant features from the preprocessed data.
3. ANFIS Model Development and Training: Initialize the ANFIS structure with a suitable number of membership functions and rules and train the ANFIS model using a hybrid learning algorithm.
4. Online Adaptation: Continuously update the ANFIS model using new data and feedback signals.
5. Control Action Generation: Generate optimal control actions based on the current state of the manufacturing process.
6. IoT Implementation: Transmit control signals to IoT-enabled devices to execute the actions.
7. Performance Evaluation: Monitor the performance of the control system and evaluate its effectiveness.

The IoT-based sensors used are vision sensors, proximity sensors, level sensors, acceleration and vibration sensors, and sound sensors. The data generated by the IoT-based sensors is transmitted wirelessly to the cloud server, where the big data is processed. The collected data are processed and stored in the MongoDB database. Data clustering and analytics are performed to predict the faults given by the sensor's data during the assembly line process. Hence, a complete history of the sensor's data is represented to the operator in real-time throughout a

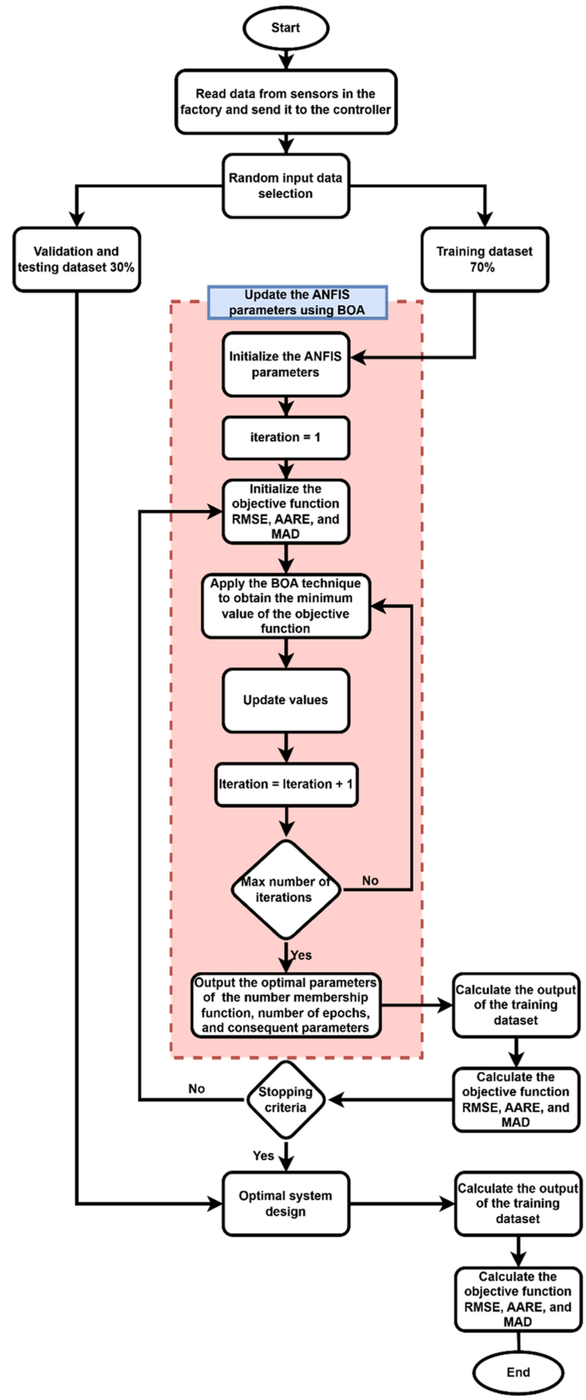


Fig. 5. Flowchart of the proposed production control method.

web-based monitoring system in addition to the fault prediction results. Smart manufacturing has several data inputs and uncertainties. The proposed controller optimally indicates the production schedule to reduce the time required and increase the financial output. The data inputs are the number and quantities of the raw materials, the number of machines in the factory, the number of production cycles, the size of the inventory, the number of processes per day, the time required for each machine per cycle, and cycle time needed each production process. Also, the number and quantities of the raw material are the uncertainties considered in this paper. The dataset of these inputs and uncertainties parameters is simulated using the MATLAB/Script program. These data are measured using sensors in smart manufacturing, and the data are arranged separately in matrices. So, this dataset contains about 540 patterns for training and testing the proposed ANFIS. The objective function of the lead time and the financial productivity are evaluated and calculated for each pattern. The dataset is divided into three parts: training, validating, and testing the proposed ANFIS controller. The training algorithm collects the training dataset to obtain the optimal production schedule solution. Then the validating dataset is applied simultaneously as training to evaluate the training quality with a new dataset. In this stage, the accuracy of the proposed ANFIS controller is improved by optimally adjusting its parameters using the BOA. Finally, the proposed ANFIS controller simulates the testing dataset to prove its effectiveness. This paper divides the dataset into; 70 % training dataset, 15 % validating dataset, and 15 % testing dataset. The simulation was conducted utilizing MATLAB R2022 on a laptop computer operating on Windows 10, 64-bit. The laptop is equipped with an Intel Core i7 processor running at 2.6 GHz and has 16 GB of RAM. The performance evaluation of the BOA (Bayesian Optimization Algorithm) was carried out through tests using 25 populations, with a maximum of 150 iterations. The dataset contains 540 data sets taken from the data collected and measured through the sensors in smart manufacturing.

To perform the best ANFIS control model for predictions, the BOA is used to optimally select and identify various affecting parameters, including the number of membership functions, the number of epochs, and the consequent parameters $\{p_i, q_i, r_i\}$. The error tolerance is set to 5 %. For the ANFIS training, the rules' parameters are updated until an error value is ensured, which must be less than the threshold value. The ANFIS parameters are updated based on the three performance indices, root mean square error (RMSE), absolute average relative error (AARE), and mean absolute deviation (MAD). These performance indices can be represented as follows [39];

$$RMSE = \sqrt{\frac{1}{K}\sum_{s=1}^{K}\left(y_{ai} - y_{pi}\right)^2} \tag{11}$$

$$AARE = \frac{1}{K}\sum_{s=1}^{K}\left|\frac{y_{ai} - y_{pi}}{\widehat{y_{pi}}}\right| * 100 \tag{12}$$

$$MAD = \frac{1}{K}\sum_{s=1}^{K}\left|y_{ai} - y_{pi}\right| \tag{13}$$

where y_{ai} and y_{pi} are the actual and predicted values, and K is the number of observations.

Also, the accuracy of the ANFIS control method can be calculated after the training, validation, and testing as follows [40],

$$Accuracy = \frac{true\ decision\ for\ production\ schedule}{total\ number\ of\ test\ data}\ \% \tag{14}$$

4. Case study and result analysis

The proposed approach develops an assessment of the supply chain (SC), starting with selecting the SC metrics, reflecting the SC practices' effectiveness and efficiency. The required input data of SC matrices were measured using IoT-based sensors at the smart manufacturing. Then, the data are sent to the data processing layer for data classification and processing using the IoT platform. In the proposed framework phases, the required data is collected by tracking the workflow of the processes with visual representation with the help of factory documents. The datasets are sent to the proposed ANFIS controller to obtain the optimal production process with an optimal production cycle. So, our proposed SC control method based on ANFIS aimed to improve the performance of the manufacturing process. Then the top SIPOC that is represented in Fig. 2 is constructed. Through this step, the different factory sectors were virtually integrated through enterprise resource planning (ERP) software supported by the smart SC.

The organization's performance is assessed using the proposed multicriteria performance evaluation matrices. Many organizations have not maximized their SC's potential because they have not developed the required performance evaluation metrics to integrate their SC to optimize effectiveness and efficiency. The required data is collected from the digital network attached to IoT-based sensors at the different stages of the SC. Then, the proposed SC performance matrices are calculated through real-time operations. After implementing a realistic case study, the proposed control method for the real-time CPPS proves its effectiveness and applicability. All SC matrices will be entered into system software and displayed in the visual display. This will empower the management to point out the unnecessary, not value-added process, activities, motion, and waiting time through SC activities, especially for paperwork flow and its actual time consumed. It will also support management in adopting and implementing every SC activity's improvement initiative.

One of our study objectives was to verify our proposed approach. The proposed approach comprises a smart manufacturing process, and an ANFIS classification algorithm implemented to evaluate the performance of the supply chain. M is an automotive spare parts manufacturer based in Egypt and has been active since 1992; it has expanded dramatically as its production is distributed to OEM Automotive Clients. It exports its products to 22 countries. It possesses ISO TS 16,949, ISO 14,001, and OHSAS 18,001 certificates. It has been available in the market since 1999. Our case study uses the proposed framework to assess the actual organization versus SC performance. In this paper, the proposed approach develops an assessment of SC metrics that aims to maximize the effectiveness and efficiency of the SC. The evaluation of a SC performance is crucial as it serves multiple purposes. Firstly, it helps in motivating employees by recognizing their strengths and providing feedback to improve in areas of weakness. Additionally, it enables the measurement of the extent to which a firm has achieved its strategic goals within the SC. These indicators measure the efficiency of different SC practices considering the process stakeholders (supplier and employee). Performance drive-oriented indicators are calculated by evaluating mainly four sectors supplier, production, inventory, and employee & learning growth performance.

This paper obtains the optimal parameters for the ANFIS control method after the data sensing, analysis, and updating using the BOA technique. The output parameters are nominated as the number of membership functions is four, the number of epochs is 500, and the consequent parameters are recorded. The BOA technique has converged during the prescribed number of iterations. However, the accuracy of the ANFIS controller-based BOA has converged at about iteration 20. Fig. 6 shows the accuracy of the proposed method over the iterations. It can be noted that the trained ANFIS-BOA has an accuracy of 99.89 %. The value of the RMSE, AARE, and MAD for the training, validating, and testing dataset are reported in Table 1.

This paper assesses the performance of smart SCs versus traditional supply chains SCs. The proposed SC performance metrics include production performance indicators such as productivity, capacity utilization, order cycle time, the effectiveness of scheduling techniques, and total supply-chain cycle time. Additionally, inventory performance indicators include inventory level and storage quality. The evaluation of supplier performance, including the supplier commitment indicator versus production productivity, is illustrated in Fig. 7(a). The results demonstrate a positive correlation between supplier commitment and production productivity. This intercorrelation extends to the inventory level, as shown in Fig. 7(b).

Fig. 7(c) highlights that production productivity improved due to the gradual enhancement of scheduling techniques. Furthermore, there is a direct correlation between production productivity and capacity utilization, as shown in Fig. 7(d). Fig. 7(e) emphasizes that employee commitment positively impacts production productivity, while the employee training indicator contributes significantly to these improvements, as demonstrated in Fig. 7(f).

Capacity utilization measures an organization's ability to optimize

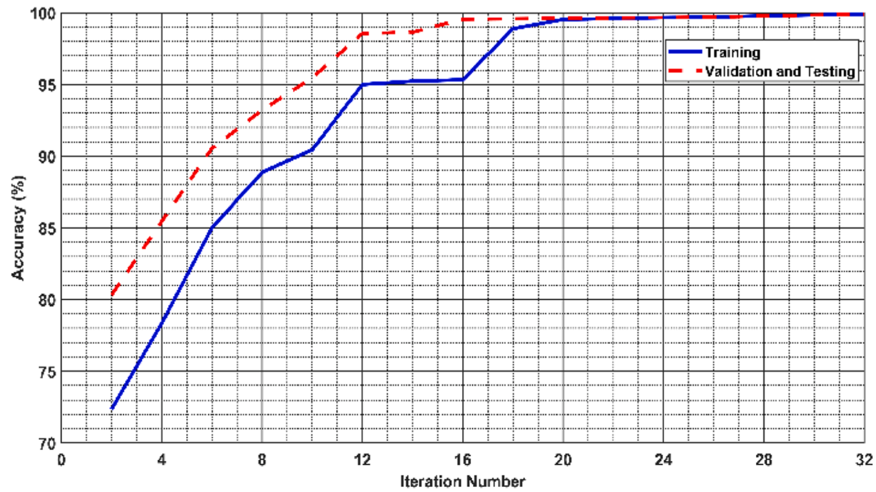


Fig. 6. Accuracy at each iteration.

Table 1
RMSE, AARE, and MAD of the ANFIS controller.

Method	RMSE	AARE	MAD
Training dataset	2.32E-4	0.0086	1.43E-4
Validating dataset	2.57E-4	0.0063	1.37E-4
Testing dataset	2.61E-4	0.0054	1.19E-4

its productivity, calculated as the ratio between theoretical and actual maximum output. Fig. 8(a) shows that idle time within the production system negatively affects capacity utilization. Moreover, production productivity enhancements indirectly influence total supply-chain cycle time, as depicted in Fig. 8(b), as well as incoming raw material quality, as shown in Fig. 9(a). These enhancements also have indirect relationships with product quality and inventory levels, as illustrated in Fig. 9(b). The analysis of inventory performance results underscores significant improvements in inventory levels due to enhanced supplier commitments and reduced lead times. As illustrated in Fig. 9(c), these indicators collectively contribute to production productivity enhancements.

Fig. 10(a) and Fig. 10(b) showcase the correlation between production productivity and financial productivity, demonstrating a direct relationship. Industry 4.0 technologies have transformed conventional production systems into smart production systems, reducing risks and improving supply chain planning. Additionally, the adoption of distributed learning and self-thinking concepts further enhances SC performance.

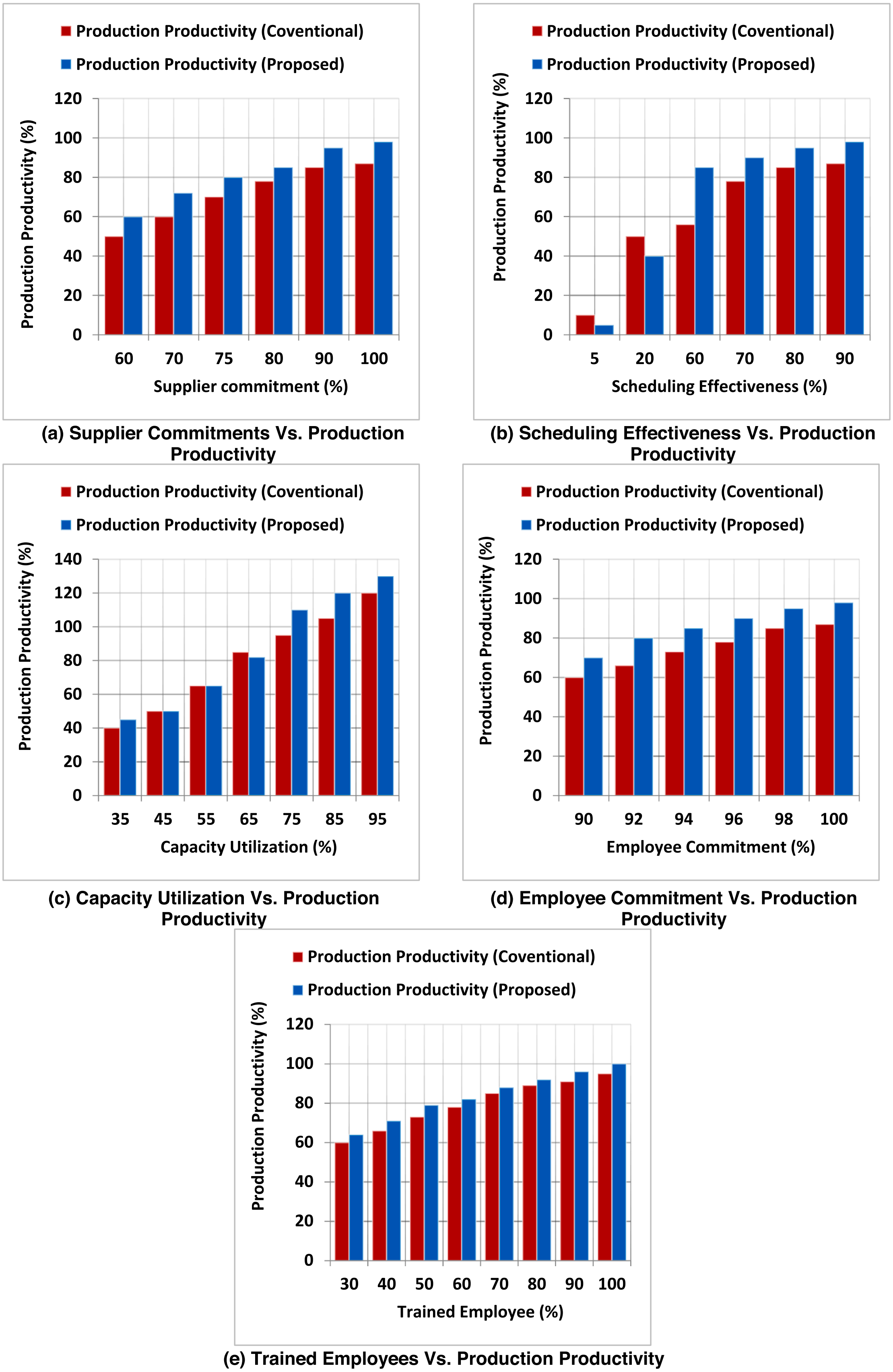
These improvements translate into financial gains, the primary goal of supply chain management. Fig. 10(c) highlights that financial performance indicators, including financial productivity and ROI, strongly correlate with customer satisfaction, order fill rates, and production productivity metrics. The SC performance evaluation results substantiate the significant impact of these improvements on SC financial performance. The financial assessment results of the traditional system versus the proposed smart system reveal enhanced customer satisfaction due to improved order fill rates and production productivity, as illustrated in Fig. 10(d). Additionally, ROI results demonstrate positive improvements driven by elevated customer satisfaction levels. In conclusion, this study validates that the proposed framework's SC evaluation results and leading performance indicators substantiate significant advancements in SC financial and operational efficiency.

Through evaluating suppliers' performance, privacy is considered a curial issue in information sharing. Due to the competitive advantage in smart manufacturing supply chain sectors, information accessibility should be kept confidential. Smart contracts would be an optimal decision to ensure data protection and enhance trust in Supply Chain. The evaluation results prove that improving supplier activities directly leads to improving supply chain performance.

The real-time assessment of production productivity related to the quality, capacity, and ability to deliver the required product to the customer provides a real enhancement in all smart manufacturing supply chain activities. Comparison between all the results of the assessment of the SC and the proposed framework of smart manufacturing SC proved outstanding enhancement which attracts customers, builds loyalty and increases customer satisfaction. The performance enhancement of the proposed framework smart manufacturing SC is because the big data are being generated with great velocity, volume, and variety in SC; extracting useful information from them empowers managers to make decisions, optimize, and improve performance. The proposed framework proves competitive advantages such as enhancing information sharing, reducing paperwork, human errors and mistakes, and increasing visibility and integration of processes.

In general, there is a relation between the performance of the SC and the system's productivity. As with the increase in productivity, the system profitability increased while decreasing the cost per unit produced. Improving processes through the proposed smart system enhances capacity utilization while reducing lost time. The proposed method strengthens the SC performance by eliminating the non-value-added steps and wasteful practices. It enhances the firm's long-term performance by improving labor productivity. Increasing labor productivity can be done using appropriate incentives and providing employees with a convenient smart working environment. Applying the proposed smart system reduces management and operation costs, labor costs, and the number of employees. This increases customer satisfaction, raises market prices, and improves financial performance. A comparison between the proposed control method and the fuzzy logic (FL) [41], artificial neural network (ANN) [42], and support vector machine (SVM) [43] is performed in Table 2. This comparison is based on the training time, testing error, and accuracy. The proposed control method improves training time and testing error; the accuracy is enhanced over the three other controllers.

The ultimate objective of our model is to assess financial performance. To achieve this, our proposed smart SC framework utilizes business intelligence tools and manual analysis of data to generate specific plans for each performance area. The knowledge obtained from the application layer is securely shared with stakeholders on a blockchain platform, ensuring traceability. Decision makers across different stages of the smart chain can compare actual performances with planned ones, enabling them to identify the root causes of poor performance and monitor their decisions. This system fosters increased competition



(a) Supplier Commitments Vs. Production Productivity

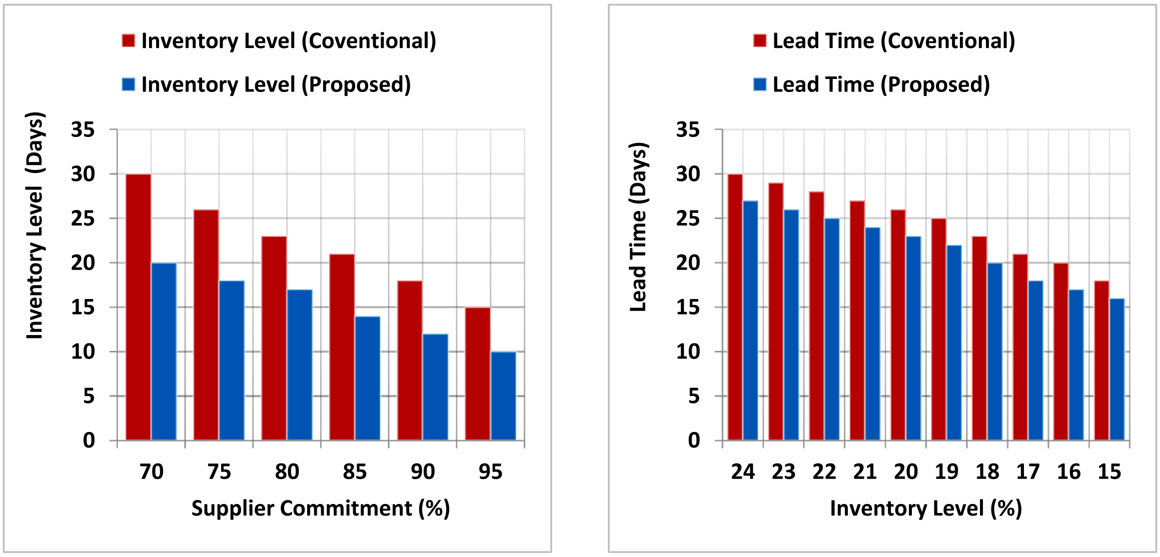
(b) Scheduling Effectiveness Vs. Production Productivity

(c) Capacity Utilization Vs. Production Productivity

(d) Employee Commitment Vs. Production Productivity

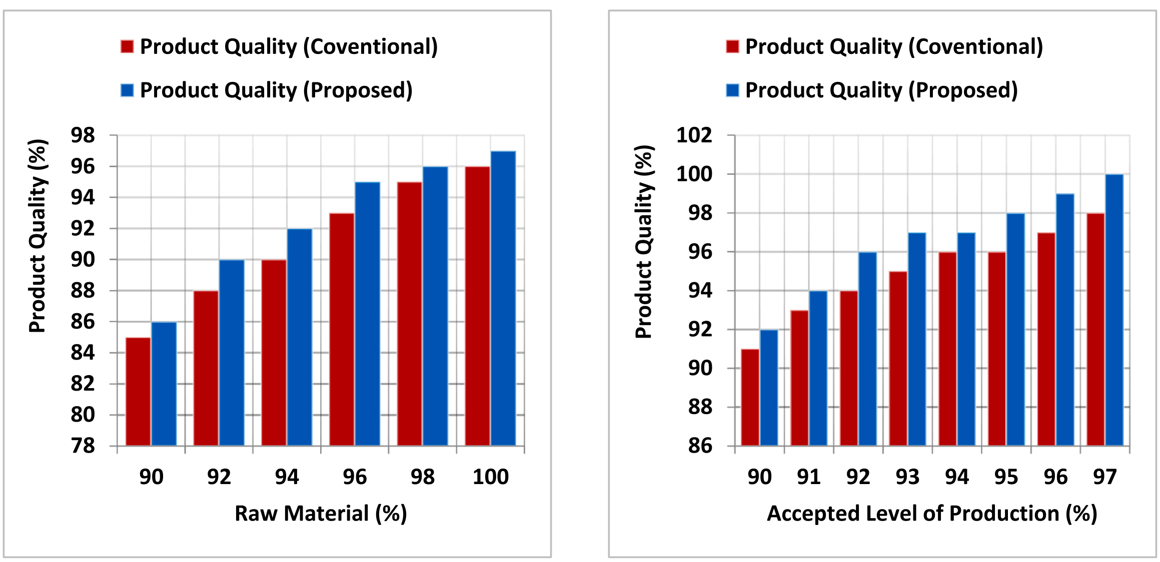
(e) Trained Employees Vs. Production Productivity

Fig. 7. Performance evaluation of production productivity through the conventional and smart SCM.



(a) Supplier Commitment Vs. Inventory Level **(b) Supplier Lead Time Vs. Inventory Level**

Fig. 8. Inventory level performance evaluation.



(a) Raw Material Vs. Product Quality **(b) Accepted Level of Production Vs. Product Quality**

Fig. 9. Performance evaluation of the product quality.

among chain members, encouraging efficient performance.

Also, different optimization algorithms are applied to prove the effectiveness of the proposed method. Genetic algorithm (GA), particle swarm optimization (PSO), and harmony search (HS) algorithm are applied. The comparative analysis is based on RMSE, AARE, MAD, and accuracy for the training dataset, as shown in Table 3.

5. Conclusions

This paper proposed an advanced control method to improve the performance of the SC. This controller is based on the ANFIS algorithm with five layers for classifying and controlling the manufacturing process. BOA has been used to obtain the optimal parameters for the ANFIS algorithm. This control method aims to enhance the performance of the CPPS while reducing the cost and time required for the SC. Also, IoT technology has been used for monitoring and data processing for all the SC steps to provide a smart manufacturing system. The proposed method has been applied and tested using a factory in Egypt to verify the applicability of the proposed controller. The results obtained with the traditional SC and applying the proposed controller are compared. The results show that the proposed method improves the lead time, productivity, and capacity utilization compared to the conventional SC. Also, the operation cost, labor cost, and the number of employees is reduced by applying the proposed method compared to the traditional SC process. Hence, the results prove the proposed method's applicability and efficacy in improving the SC's performance.

CRediT authorship contribution statement

Mona A. AbouElaz: Writing – original draft, Visualization, Data curation, Conceptualization. **Bilal Naji Alhasnawi:** Writing – review & editing, Validation, Formal analysis, Conceptualization. **Bishoy E.**

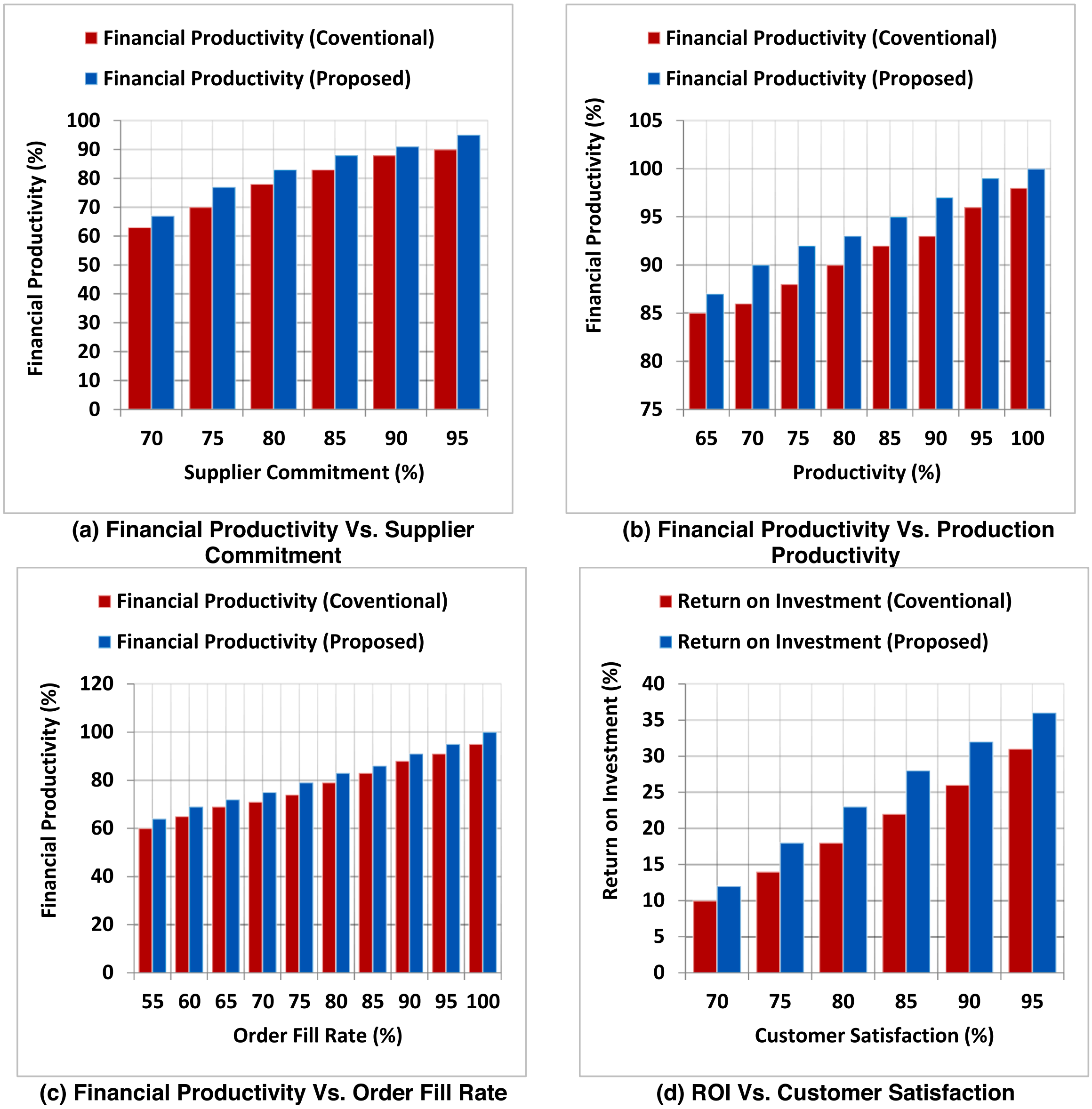


Fig. 10. Financial performance evaluation.

Table 2
The Comparative results for different control methods.

Method	training time (s)	Testing error (%)	Accuracy (%)
FL	119	3.56	94.56
ANN	103	2.12	95.32
SVM	99	1.67	97.72
Proposed Method	83	0.31	99.89

Table 3
The Comparative results for Different optimization algorithms.

Method	RMSE	AARE	MAD	Accuracy
GA	4.53E-3	0.0650	3.89E-3	97.34
PSO	3.57E-3	0.0238	2.31E-3	97.89
HS	4.98E-4	0.0173	3.14E-4	98.23
Proposed Method	2.32E-4	0.0086	1.43E-4	99.89

Sedhom: Writing – original draft, Supervision, Project administration, Methodology. **Vladimír Bureš:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The research has been partially supported by the Faculty of Informatics and Management UHK excellence project “Methodological perspectives on modeling and simulation of hard and soft systems 2″.

Data availability

Data will be made available on request.

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