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Smart Manufacturing Systems: AI-Driven Optimization of Industrial Processes

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Abstract

Smart manufacturing systems in Industry 4.0 rely on interconnected, data-driven processes to enhance productivity and efficiency. However, conventional rule-based and single-model approaches fail to capture dynamic, high-dimensional industrial data, limiting optimization and adaptability. This research proposes an Artificial Intelligence (AI)-driven model for optimizing industrial processes through intelligent and adaptive decision-making. Multi-source datasets comprising Internet of Things (IoT) sensor streams, machine operation logs, and production performance metrics are utilized. The dataset is preprocessed by using Z-score normalization, and Fast Fourier Transform (FFT) is used for feature extraction to convert time-domain sensor and machine operation data into the frequency domain. The proposed framework utilizes a Non-Dominated Genetic-based Adaptive Light Gradient (NG-ALG), designed to balance exploration and exploitation in industrial optimization while handling conflicting objectives such as cost, energy, and throughput. It integrates Non-dominated Sorting Genetic Algorithm II (NSGA-II) to optimize industrial process parameters by balancing conflicting goals, such as cost reduction, energy efficiency, and production throughput, thereby facilitating intelligent decision-making in Industry 4.0 environments. It also incorporates Adaptive Light Gradient Boosting Machine (Adaptive LightGBM) to provide highly accurate predictions of industrial process behavior and to support AI-driven optimization in smart manufacturing systems. Experimental results demonstrate improved production efficiency, reduced downtime, and enhanced resource utilization with a mean absolute error (MAE) of 0.060, a Mean Squared Error (MSE) of 0.008 and R^2 of 0.895 which was stimulated in Python. The proposed method enables scalable, adaptive, and data-driven optimization, contributing to intelligent autonomous and efficient smart manufacturing systems.

Keywords: Smart Manufacturing, Artificial Intelligence, Industrial Processes, Production Efficiency.

1.Introduction

Due to a number of factors, including digitization, globalization, and disruptors like the coronavirus epidemic that forced industrial operations to adopt more flexible strategies, global production has rapidly changed [1]. In response to the increasing demands of consumers for rapid delivery, shorter product life cycles, and mass customization, businesses are implementing more agile manufacturing processes. As a result, Industry 4.0 has created an integrated digitalization platform that includes digital twins, cloud computing, IoT, cyber-physical production systems, and smart sensors [2]. Increasing manufacturing efficiency, cutting waste, making sure production systems satisfy customer requests, encouraging industry sustainability, and boosting competitiveness have all been made possible by the integration of smart technologies with lean manufacturing techniques. Smart manufacturing systems can make independent judgments regarding production processes thanks to artificial intelligence (AI), machine learning (ML), deep learning (DL), and data analysis. In Cyber-Physical Systems and IoT contexts, AI and ML are used for maintenance, resource allocation, monitoring, simulation-based optimization, and anomaly detection [3].AI and ML models and simulation techniques like digital twin-based decision-making systems, agent-based modeling, and data-driven analytics can be used in improving operation efficiency and enhancing adaptability in manufacturing systems [4]. Moreover, ML approaches are increasingly applied to cybersecurity threat detection and prediction as well as workflow optimization in industries. DL and Big Data analytics assist in process planning and optimization in logistics, as well as contribute to decision intelligence in the context of Industry 4.0. Cybersecurity challenges related to the use of ICPS in smart manufacturing call for advanced threat modeling for vulnerability analysis and risk assessment [5]. However, to develop intelligent and autonomous manufacturing systems in the future, a number of significant issues must be resolved. Interoperability between digital and physical systems, scalability of the AI model employed, and heterogeneity of data sources are some of the main obstacles [6]. These days, most models utilized in manufacturing processes are conceptual or simulation models that lack real-world industrial examples [7]. Other problems include the rigidity of AI and ML systems, high implementation costs, cybersecurity and data security challenges, and a lack of a clear framework [8].

Research aim: This research looks into the advantages of combining AI with Industry 4.0 technology to create effective and flexible smart manufacturing systems. Finding some of the main problems with intelligent manufacturing systems is another goal of this research.

Research organization: The research has been divided into several sections. In the framework of Industry 4.0, Section 1 covers the idea of smart manufacturing systems and the importance of AI-based optimization for enhancing production processes. Artificial intelligence, machine learning, deep learning, digital twins, the Internet of Things, and decision support systems are just a few of the subjects covered in Section 2's pertinent literature analysis on digital transformation in the industrial sector. Section 3 offers details on the research's methodology While Section 4 examines the performance and assesses the accuracy of the current intelligent manufacturing systems. Key findings and recommendations for further research round out Section 5.

2. Related work

The Table 1 highlights the recent study on Industry 4.0, which focuses on intelligent decision-making systems, smart manufacturing, predictive maintenance, and digital transformation models. The methodologies highlighted include MCDM, ML, and blockchain. Some of the findings include improvements in efficiency, sustainability, and predictive accuracy, although there remain some limitations due to validation, data problems, and scalability issues.

Table 1: Previous research on Industry 4.0 based Smart Manufacturing, and Predictive Frameworks

Ref.	Research Aim	Techniques	Experimental Results	Limitations
[9]	Evaluate digital technology adoption in smart manufacturing SMEs.	q-Rung Orthopair Fuzzy Sets for Multi-Criteria Decision-Making (MCDM with q-ROFS)	Stable ranking and robust decision evaluation.	No data integration; limited validation.
[10]	Apply Industry4.0 technologies for smart manufacturing automation.	Frameworks for AI, IoT, cloud, Big Data (BD), Cyber-Physical Systems	Improved efficiency, maintenance, and production quality.	Cybersecurity, high cost, interoperability, and privacy issues.

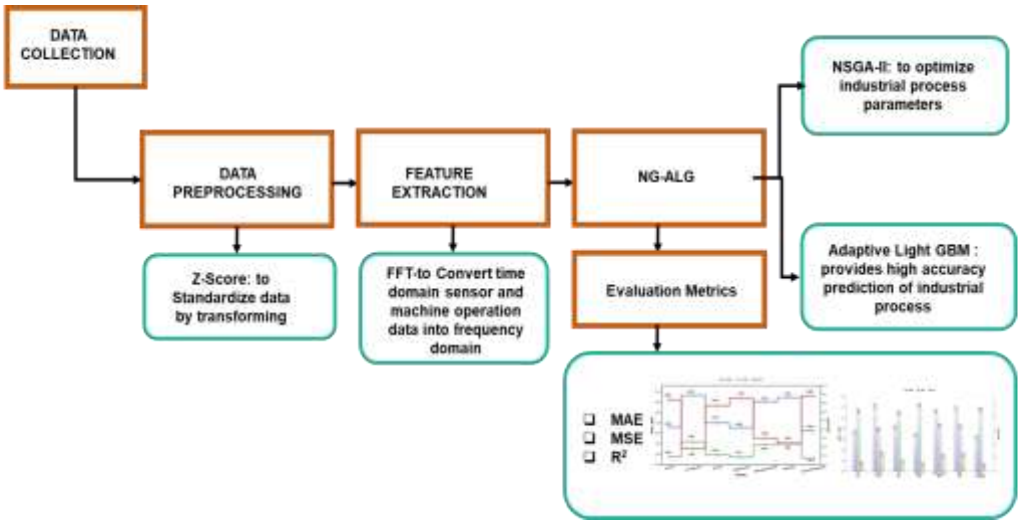
		(CPS), and Virtual Reality (VR)		
[11]	Improve cleaner production using lean manufacturing and Industry4.0.	Lean tools integrated with CPS, AI, IoT, Flexible Manufacturing System (FMS)	Enhanced productivity, safety, and operational efficiency.	Limited case studies; lacks optimization.
[12]	Analyze barriers to I4.0 adoption in Small and Medium-sized Enterprise (SMEs).	Review of the literature and examination of secondary data	Increased productivity but uneven SME adoption.	High cost, infrastructure, and scalability challenges.
[13]	Enable mass customization using blockchain in I4.0.	Blockchain-based production coordination model	Better transparency, traceability, and planning.	No real-world implementation; scalability concerns.
[14]	Develop adaptive energy models in Digital Twin (DT)-based industries.	Data-driven adaptive DT energy modeling	More than 2× higher accuracy than static models.	Needs validation for multi-machine real environments.
[15]	Integrate Automated Guided Vehicles (AGVs) and IoT for lean automation.	Socio-Technical Systems (STS) framework with AGVs and IoT	Improved human–technology operational alignment.	Limited industrial validation and workforce analysis.
[16]	Develop predictive maintenance DSS with limited labels.	Cloud-based Decision Support System (DSS) with ML and feature extraction	MAE: 0.089, MSE: 0.018, low latency.	Scalability and robustness need improvement.

Research Gap: The suggested research seeks to solve the problems of insufficient adaptability and scalability of the existing AI-based smart manufacturing system. These systems lack adaptability due to the inability to deal with different data sets and changing environments. As such, the suggested solution is an AI-based smart manufacturing system that will use data analysis techniques and NG-ALG in order to optimize, adapt, and make decisions scalable.

3. Methodology

The suggested approach to smart manufacturing based on NG-ALG considers the analysis of industrial processes via data analytics and machine learning techniques. Data collection and preprocessing are carried out to ensure consistency in the quality of the collected information; then, feature extraction and application of machine learning techniques are used to recognize patterns for decision making. The method is flexible to adapt to production dynamics (Figure 1).

Figure 1: Methodology of proposed model



3.1 Dataset description: The dataset used for optimizing the AI-enabled smart manufacturing system has been obtained from an open source database repository (https://www.kaggle.com/datasets/colabsss/smart-manufacturing-process-dataset). The dataset contains 10,000 samples from connected machines working in the manufacturing environment. The data set comprises machine status, IoT sensors reading, efficiency, energy usage, and performance measures. The dataset is splited into training 80% and test 20% data sets. This data set can be used for academic studies related to smart manufacturing systems, analytics, process optimization, and machine learning-based decision making in Industry 4.0.

3.2 Data preprocessing using Z-Score: The Z-score method is a statistical tool that helps to convert the distribution in the dataset into a standardized form where the mean equals zero and the standard deviation is equal to one. The process of Z-score normalization is employed for the standardization of data to make sure that all the data becomes uniform.

$$X_{score} = \frac{rss(n)-\mu}{\sigma} \quad (1)$$

$$rss_{j,i} = [rss(1), rss(2), \ldots rss(N)] \qquad for\ 1 \le n \le N \quad (2)$$

Equation (1) and (2) X_{score} defines the Z-score for the nth observation, where $rss(n)$ is the residual sum of squares for that point. Here, μ represents the mean of all RSS values, and σ is their standard deviation. The vector notation $rss_{j,i} = [rss(1), rss(2), \ldots rss(N)]$ lists all RSS values for indices j and i, where N is the total number of observations, allowing for the standardization of errors. This facilitates comparison of how extreme each residual is within the overall dataset.

3.3 Feature extraction using FFT: The FFT in Smart Manufacturing Systems is to transform raw time-domain industrial sensor data into frequency-domain representations that reveal hidden operational patterns, enabling accurate feature extraction for AI-driven optimization, predictive analytics, and industrial decision-making. The equation (3), defines the transformation from time-domain to frequency-domain in signal processing.

$$H_n = \sum_{k=0}^{N-1} W^{nk} h_k \quad (3)$$

Here, H_n represents the Fourier coefficient, indicating the magnitude and phase of the nth frequency component of the industrial signal for feature extraction in smart manufacturing. h_k refers to the input time-domain signal, such as IoT sensor data from industrial equipment. $\sum_{k=0}^{N-1}$ represents summation over all time-domain samples. N denotes the total number of samples in the evaluation window, while k and n are index variables for the time-domain and frequency-domain components, respectively. W is the complex twiddle factor which aids in converting the time-domain data into its frequency representation through the complex exponential basis function W^{nk}.

3.4 AI-driven smart manufacturing system using NG-ALG algorithm: The AI-driven smart manufacturing system using the NG-ALG algorithm integrates advanced ML and evolutionary optimization to enhance industrial process efficiency and decision-making. NG to perform multi-objective optimization by identifying Pareto-optimal solutions while maintaining diversity among competing industrial objectives and ALG to provide accurate predictive modeling of industrial processes, guiding optimization and intelligent decision-making in smart manufacturing systems.

3.4.1 Adaptive LightGBM-Predictive Learning for Smart Manufacturing: Adaptive LightGBM is an improved gradient boosting machine learning technique that uses optimal decision tree learning to repeatedly improve prediction accuracy in order to effectively handle large-scale industrial datasets. Its objective is to model complex nonlinear relationships in IoT-based production data to enable accurate prediction of system behavior, process performance, and operational outcomes. This supports decision-making and contributes to AI-driven optimization of industrial processes by improving efficiency, adaptability, and predictive capability which present in equation (4).

$$F_T(x) = \sum_{t=0}^{T} F_t(x)\,, F_t \in \Theta \tag{4}$$

$F_T(x)$ Represents the final predictive model output (strong learner) obtained by combining multiple weak learners. It provides the ultimate optimum prediction for industrial process behavior in smart manufacturing systems within the specified environment. $F_t(x)$ denotes the $t\ th$ base learner (weak model), typically a decision tree in boosting methods like LightGBM, which contributes incrementally to improving prediction accuracy. $\sum_{t=0}^{T}$ represents summation over all weak learners in the ensemble, t represents the iteration index or boosting round, indicating each step of model improvement. T Total number of iterations or weak learners used in the ensemble model. x Input feature vector derived from industrial data. $F_t \in \Theta$ means the t-th weak learner is chosen from the set of all possible learners Θ where, Θ represents the function space used by the model for learning patterns in data.

3.4.2 NSGA-II for Optimization in Smart Manufacturing: NSGA-II is an evolutionary multi-objective optimization technique designed for handling optimization problems with multiple and conflicting objectives. NSGA-II creates a set of solution vectors and uses NG to compute Pareto-optimal fronts, keeping in mind diversity in solutions using crowding distance. NSGA-II optimizes industrial process parameters considering various conflicting objectives such as minimizing cost, energy efficiency, and maximizing production rates.

$$cd(i) = \sum_{i=1}^{k} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{max} - f_j^{min}} \tag{5}$$

The crowding distance of the i solution, denoted by $cd(i)$ in Equation (5), is utilized in NSGA-II to preserve variety among solutions in the Pareto front for multi-objective optimization. Here, (i) stands for the present solution's index, (j) for the objective function's index, and (k) for the total number of objectives taken into consideration. After sorting, the values of the j objective function for the subsequent and preceding neighboring solutions are denoted by f_j^{i+1} and f_j^{i-1} ,respectively. The maximum and minimum values of the j objective among all solutions are denoted by f_j^{max} and f_j^{min}, which are used for normalization.

Algorithm 1: AI-Driven Smart Manufacturing Optimization using NG-ALG

Input:
D → Dataset of industrial processes, MaxIter → Maximum iterations for NSGA-II, N → Population size for NSGA-II, lb, ub → Bounds for decision variables, T → Total number of boosting iterations in LightGBM
Output:
O → Optimized industrial process parameters and predictive model
Begin
1. Load dataset D
2. Data Preprocessing using Z-Score:
For each feature F in D:
Compute Z-score:
$X_{score} = \frac{rss(n) - \mu}{\sigma}$
Handle missing values, if any
End For
3. Feature Extraction using FFT:
For each time-domain signal h_k in D:
Transform to frequency-domain:
$H_n = \sum_{k=0}^{N-1} W^{nk} h_k$
End For

Select dominant frequency components as feature set F
4. Predictive Modeling using Adaptive LightGBM:
Initialize base learners Ft in Θ
For t = 0 to T:
Train weak learner Ft(x) on features F
Update ensemble prediction: $F_T(x) = \sum_{t=0}^{T} F_t(x)$
End For
Evaluate prediction accuracy and update model
5. Multi-objective Optimization using NSGA-II:
Initialize population Bj = lb + rand(0,1)*(ub-lb)
For t = 1 to MaxIter:
Evaluate objectives (cost, energy, throughput) for each solution
Perform non-dominated sorting to form Pareto fronts
Compute crowding distance:
$cd(i) = \sum_{i=1}^{k} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{max} - f_j^{min}}$
Select solutions for next generation based on rank and diversity
Apply crossover and mutation to generate new solutions
End For
6. Output optimized parameters O and predictive model FT(x)
End

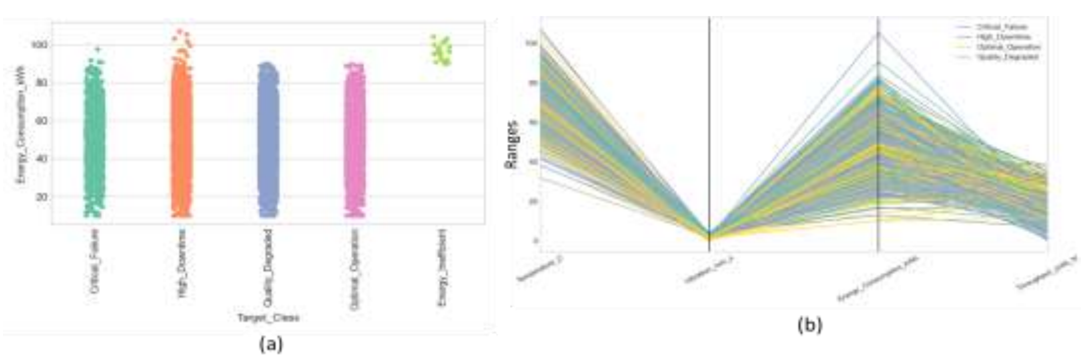
The proposed Algorithm 1 integrates data-driven analytics, ML, and multi-objective optimization to enhance smart manufacturing systems. It preprocesses industrial data using Z-score normalization, extracts meaningful features through FFT, and predicts system behavior using Adaptive LightGBM. NSGA-II is then applied to optimize conflicting objectives such as cost, energy consumption, and production throughput, providing, intelligent decision-making for efficient and adaptive industrial process management.

4. Results and Discussion

Experimental results for the suggested NG-ALG model are discussed in this section. Experimental results also involve the comparison of the NG-ALG model with ML models like (Random Forest (RF), Linear Regression with Ridge (LR Ridge)**,** XGBoost, Regression Tree (RT), Support Vector Machine with Gaussian (SVR Gaussian), Multi-Layer Perceptron (MLP) [16]). The entire experimental approach was done in the Python programming language.

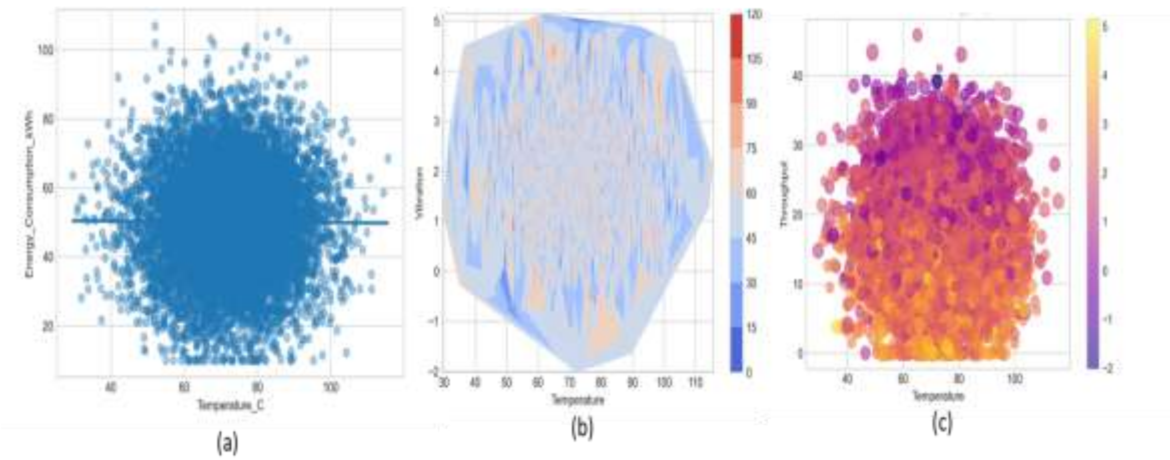
4.1Data feature exploration analysis: Figure2(a) shows the comparison of categorical feature distributions with varied spreads and concentrations for each group. This approach helps in determining the consistency of classes and finding any outliers or imbalances between different feature sets. Figure 2(b) depicts the analysis of multivariate dependencies for various features together that help in observing dependencies between the features and their variances. The analysis makes the interpretation of high dimensional data easy and fast through the identification of similarities and dissimilarities between variables.

Figure 2: (a) Comparing categorical data distributions; (b) Analyzing multivariate relationships across features



The plot in Figure 3(a) represents the relationship between temperature and energy, and the clustering of points in the graph represents the stability of the changes that occur over the observed temperatures. It is important to note that the clustering suggests that energy values will largely be within moderate temperatures, indicating the validity of the data being analyzed. In the case of Figure 3(b), the changing feature value over the temperature range provides useful information in detecting inconsistencies or fluctuations in the data. This is essential in determining the reaction of feature values to environmental changes. The use of color in Figure 3(c) indicates different magnitudes in the data set. Different color ranges indicate different magnitudes and distributions of the data points.

Figure 3:(a) Correlating temperature with energy output ;(b) Visualizing value distribution across temperature range;(c) Mapping intensity variation using color scaling



4.2 Metric Description

MAE: The average absolute error between the actual and forecasted values is measured. This statistic provides a clear picture of forecast accuracy because it does not give errors of greater magnitude any additional weight.
MSE: It is the average squared error between the actual and anticipated values. When it comes to identifying and mitigating significant errors, squared errors are a valuable indicator since they give the larger errors more weight.
Coefficient of Determination (R^2): It represents the proportion of variance in the actual values explained by the regression model. A higher value of R^2, closer to 1, suggests that, model explains the variations in the data effectively, whereas a smaller value signifies poor performance.

4.3 Performance Evaluation and comparison

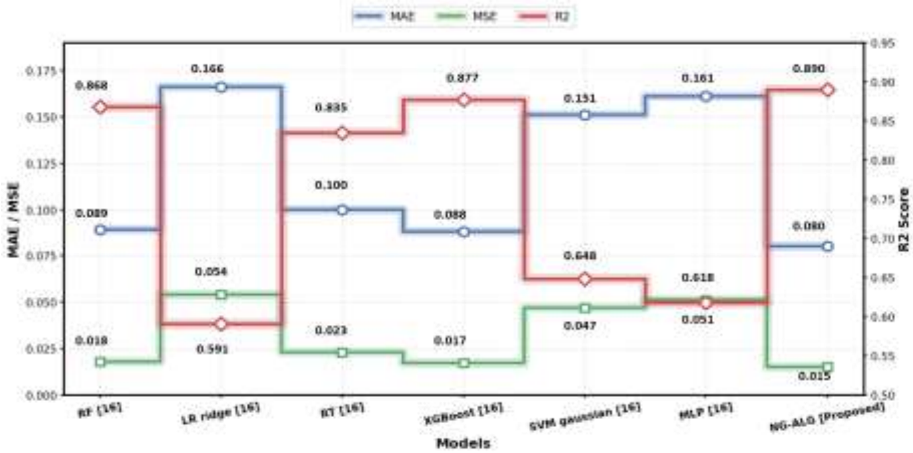
With the help of various experiments carried out using the different machine learning models, which have been trained using the present dataset, it has been observed that the NG-ALG model performs better than existing datasets [16]. Hence, it is more suitable for being used in training and validation of decision support systems. The NG-ALG model is able to achieve a high R^2 score of 0.890, compared to RF (0.868), RT (0.835), SVM Gaussian (0.648), MLP (0.618), and LR Ridge (0.591). As far as accuracy in prediction is concerned, the NG-ALG model achieves a lower MAE score of 0.080 and MSE score of 0.015; while XGBoost is the second best with MAE of 0.088 and MSE of 0.017 (Figure 4 and table 2).

Table 2: Performance evaluation of the proposed model is trained using the existing dataset

Model	**MAE**	**MSE**	**R^2**
RF [16]	0.089	0.018	0.868
LR ridge [16]	0.166	0.054	0.591
RT [16]	0.100	0.023	0.835
XG Boost [16]	0.088	0.017	0.877
SVM gaussian [16]	0.151	0.047	0.648
MLP [16]	0.161	0.051	0.618

NG-ALG [proposed]	0.080	0.015	0.890

Figure 4: Representation of the existing and proposed NG-ALG model trained in the existing dataset.

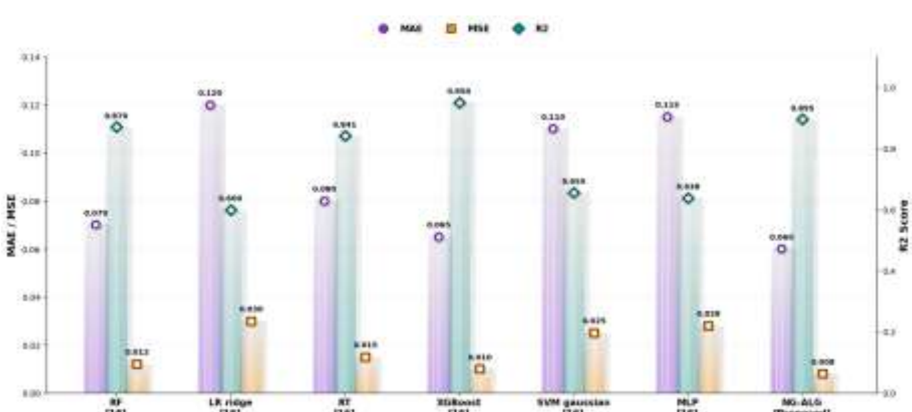


By achieving an MAE of 0.060 and MSE of 0.008, the proposed NG-ALG model outperforms other machine learning models that have been trained using the smart manufacturing process dataset, including RF, LR ridge, RT, SVM gaussian, and MLP. Nevertheless, the NG-ALG model can reduce the local errors with an MAE of 0.120 (LR ridge) and an MSE of 0.030 (LR ridge), despite the XG Boost model's superior R^2 value of 0.950 compared to the NG-ALG's 0.895 (Figure 5 and table 3).

Table 3: Comparison of existing and proposed models trained on the smart-manufacturing-process-dataset

Model	**MAE**	**MSE**	**R^2**
RF [16]	0.070	0.012	0.870
LR ridge [16]	0.120	0.030	0.600
RT [16]	0.080	0.015	0.841
XG Boost [16]	0.065	0.010	0.950
SVM gaussian [16]	0.110	0.025	0.655
MLP [16]	0.115	0.028	0.638
NG-ALG [proposed]	0.060	0.008	0.895

Figure 5: Presentation of existing and NG-ALG models on smart-manufacturing process dataset



The current predictive maintenance techniques such as RF, RT, and SVM are restricted to static data sets and traditional learning, leading to inaccuracy and inability to adapt in dynamic situations [16]. The proposed NG-ALG algorithm tries to address these challenges through the use of ALG in conjunction with NSGA-II, allowing for increased predictive accuracy based on the complex interrelations of the data sets.

5. Conclusion

This research introduces an innovative approach in which the proposed AI-based smart manufacturing system employs NSGA-II for multi-objective optimization, FFT-based feature extraction, Z-score normalization, and Adaptive Light GBM predictive models. The purpose of such an implementation is to enhance decision-making abilities and, simultaneously, increase industrial productivity, energy consumption, and cost effectiveness through the analysis of different IoT sensors. With the MAE being equal to 0.060, MSE to 0.008, and R2 to 0.895, the experimentally verified research demonstrates the increase in the efficiency of production, reduction in downtime, and resource utilization. These results were achieved due to a Python model. One of the model limitations is a reliance on pre-defined feature engineering approaches such as FFT that could fail to find any non-linear patterns. Besides that, the accuracy of the outcomes received with the help of the model greatly depends on past sensor data availability. Another limitation could also come from the necessity to tune model parameters and possible noise that could lead to computational complexity when the model works on a bigger scale.

References

1. Attaran, M., Attaran, S. and Celik, B.G., 2023. The impact of digital twins on the evolution of intelligent manufacturing and Industry 4.0. Advances in Computational Intelligence, 3(3), p.11. https://doi.org/10.1007/s43674-023-00058-y
2. Göppert, A., Grahn, L., Rachner, J., Grunert, D., Hort, S. and Schmitt, R.H., 2023. Pipeline for ontology-based modeling and automated deployment of digital twins for planning and control of manufacturing systems. Journal of Intelligent Manufacturing, 34(5), pp.2133-2152. https://doi.org/10.1007/s10845-021-01860-6
3. Mahmoodi, E., Fathi, M., Tavana, M., Ghobakhloo, M. and Ng, A.H., 2024. Data-driven simulation-based decision support system for resource allocation in industry 4.0 and smart manufacturing. Journal of manufacturing systems, 72, pp.287-307. https://doi.org/10.1016/j.jmsy.2023.11.019
4. Shkarupylo, V., Alsayaydeh, J.A.J., Yusof, M.F.B., Oliinyk, A., Artemchuk, V. and Herawan, S.G., 2024. Exploring the potential network vulnerabilities in the smart manufacturing process of Industry 5.0 via the use of machine learning methods. IEEE Access, 12, pp.152262-152276. https://doi.org/10.1109/ACCESS.2024.3474861
5. Jbair, M., Ahmad, B., Maple, C. and Harrison, R., 2022. Threat modelling for industrial cyber physical systems in the era of smart manufacturing. Computers in Industry, 137, p.103611. https://doi.org/10.1016/j.compind.2022.103611
6. Lăzăroiu, G., Andronie, M., Iatagan, M., Geamănu, M., Ștefănescu, R. and Dijmărescu, I., 2022. Deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in the internet of manufacturing things. ISPRS International Journal of Geo-Information, 11(5), p.277. https://doi.org/10.3390/ijgi11050277
7. Valaskova, K., Nagy, M., Zabojnik, S. and Lăzăroiu, G., 2022. Industry 4.0 wireless networks and cyber-physical smart manufacturing systems as accelerators of value-added growth in Slovak exports. Mathematics, 10(14), p.2452. https://doi.org/10.3390/math10142452
8. Florescu, A. and Barabas, S., 2022. Development trends of production systems through the integration of lean management and industry 4.0. Applied Sciences, 12(10), p.4885. https://doi.org/10.3390/app12104885
9. Yang, L., Zou, H., Shang, C., Ye, X. and Rani, P., 2023. Adoption of information and digital technologies for sustainable smart manufacturing systems for industry 4.0 in small, medium, and micro enterprises (SMMEs). Technological Forecasting and Social Change, 188, p.122308. https://doi.org/10.1016/j.techfore.2022.122308
10. Singh, A., Madaan, G., Hr, S. and Kumar, A., 2023. Smart manufacturing systems: a futuristics roadmap towards application of industry 4.0 technologies. International Journal of Computer Integrated Manufacturing, 36(3), pp.411-428. https://doi.org/10.1080/0951192X.2022.2090607

11. Tripathi, V., Chattopadhyaya, S., Mukhopadhyay, A.K., Sharma, S., Li, C. and Di Bona, G., 2022. A sustainable methodology using lean and smart manufacturing for the cleaner production of shop floor management in industry 4.0. Mathematics, 10(3), p.347. https://doi.org/10.3390/math10030347
12. Nagy, M., Lăzăroiu, G. and Valaskova, K., 2023. Machine intelligence and autonomous robotic technologies in the corporate context of SMEs: Deep learning and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems. Applied Sciences, 13(3), p.1681. https://doi.org/10.3390/app13031681
13. Perez, A.T.E., Rossit, D.A., Tohme, F. and Vasquez, O.C., 2022. Mass customized/personalized manufacturing in Industry 4.0 and blockchain: Research challenges, main problems, and the design of an information architecture. Information Fusion, 79, pp.44-57. https://doi.org/10.1016/j.inffus.2021.09.021
14. Bermeo-Ayerbe, M.A., Ocampo-Martinez, C. and Diaz-Rozo, J., 2022. Data-driven energy prediction modeling for both energy efficiency and maintenance in smart manufacturing systems. Energy, 238, p.121691. https://doi.org/10.1016/j.energy.2021.121691
15. Vlachos, I.P., Pascazzi, R.M., Zobolas, G., Repoussis, P. and Giannakis, M., 2023. Lean manufacturing systems in the area of Industry 4.0: a lean automation plan of AGVs/IoT integration. Production planning & control, 34(4), pp.345-358. https://doi.org/10.1080/09537287.2021.1917720
16. Rosati, R., Romeo, L., Cecchini, G., Tonetto, F., Viti, P., Mancini, A. and Frontoni, E., 2023. From knowledge-based to big data analytic model: a novel IoT and machine learning based decision support system for predictive maintenance in Industry 4.0. Journal of Intelligent Manufacturing, 34(1), pp.107-121. https://doi.org/10.1007/s10845-022-01960-x