

A HYBRID FUZZY C-MEANS–ANFIS MODEL TO PREDICT PRODUCTION LEAD TIME UNDER MACHINE FAILURE, STOCHASTIC BOTTLENECK AND OTHER UNCERTAINTIES

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ABSTRACT

Production lead time is difficult to predict when multiple sources of uncertainty occur simultaneously. Machine failures, stochastic bottlenecks, setup-time variability, processing-time variability, and work-in-process make deterministic estimates inadequate for representing actual production conditions. This study develops a hybrid Fuzzy C-Means (FCM)–Adaptive Neuro-Fuzzy Inference System (ANFIS) model to predict production lead time in a multi-stage manufacturing environment. A simulation model generates 5,000 production observations under stochastic operating conditions. FCM identifies groups of similar production states, and cluster-specific ANFIS models are trained to capture nonlinear relationships between operating conditions and lead time. The proposed model is evaluated against linear regression, artificial neural network, random forest, XGBoost, and standalone ANFIS benchmarks. The FCM–ANFIS model achieves an RMSE of 2.84 hours, MAE of 2.11 hours, and MAPE of 4.37%, yielding the lowest overall prediction error among the compared models. Sensitivity analysis identifies MTTR and bottleneck waiting time as the strongest positive drivers of predicted lead time.

Original research



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1. INTRODUCTION

Accurate prediction of production lead time is a fundamental requirement for production planning, scheduling optimization, capacity management, and customer delivery commitment in modern manufacturing systems. In recent years, the increasing complexity of production environments, coupled with the emergence of Industry 4.0 technologies, has significantly amplified the uncertainty associated with manufacturing operations. Consequently, traditional deterministic lead-time estimation approaches are no longer capable of providing reliable predictions in dynamic and stochastic production settings. Production lead time is affected by multiple sources of uncertainty that interact in a highly nonlinear

manner. Among the most influential factors are machine breakdowns, stochastic bottleneck behavior, setup time variability, processing time fluctuations, and work-in-process congestion. These factors not only affect individual workstations but also propagate throughout the production system, creating complex dependencies that are difficult to model using conventional analytical techniques.

Existing studies on production lead-time prediction have predominantly focused on deterministic scheduling assumptions or isolated uncertainty sources. Most available models assume fixed processing times, neglect machine reliability effects, or simplify bottleneck dynamics. Furthermore, statistical and regression-based approaches often require strong assumptions regarding

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linearity, independence, and data distribution, which rarely hold in real manufacturing environments. Although machine learning techniques have recently demonstrated promising predictive capabilities, many existing models operate as black-box systems and fail to adequately capture the fuzzy and uncertain nature of manufacturing processes. Another important limitation in the current literature is the insufficient integration of fuzzy reasoning and machine learning techniques for lead-time prediction under multiple simultaneous uncertainty sources. Production systems generate heterogeneous operational conditions, making it difficult for a single prediction model to accurately represent all manufacturing states. Consequently, the predictive performance of conventional linear regression, Artificial Neural Networks (ANNs), random forest, XGBoost, and standalone Adaptive Neuro-Fuzzy Inference System (ANFIS) models often deteriorates when faced with highly diverse and uncertain production scenarios. To address these limitations, this study proposes a novel hybrid intelligent prediction model that integrates Fuzzy C-Means (FCM) clustering and ANFIS for manufacturing lead-time prediction. The proposed approach first employs FCM to identify homogeneous operational states and reduce data heterogeneity through fuzzy partitioning. Subsequently, cluster-specific ANFIS models are trained to learn complex nonlinear relationships among machine failures, bottleneck waiting times, setup times, processing times, and production lead time. Because access to detailed industrial production data is often limited by confidentiality, this study uses a simulation-based manufacturing environment. The simulation generates 5,000 observations while representing the uncertainty sources defined in the research model: machine failures, bottleneck waiting, setup-time variation, processing-time variation, and WIP fluctuations. Using simulated data also makes it possible to evaluate the proposed model under controlled and repeatable operating conditions.

The main research question is: "Can a hybrid FCM–ANFIS model provide more accurate and robust predictions of production lead time under simultaneous uncertainties arising from machine breakdowns, stochastic bottlenecks, setup-time variability, and processing-time fluctuations compared with conventional machine learning approaches?"

The answer to this question contributes both theoretically and practically. From a theoretical perspective, the study extends intelligent manufacturing research by integrating fuzzy clustering and neuro-fuzzy learning within a unified prediction architecture. From a practical perspective, the proposed model provides production managers with a reliable decision-support tool for proactive scheduling, resource allocation, and resilient manufacturing planning in uncertain production environments.

2. LITERATURE REVIEW

ANFIS has become one of the most influential intelligent modeling techniques for nonlinear prediction and decision-making problems. The pioneering work of Jang (1993) introduced the ANFIS architecture by integrating the learning capability of artificial neural networks with the reasoning mechanism of fuzzy inference systems. The study addressed the challenge of modeling complex nonlinear systems where traditional mathematical formulations were insufficient. Through a hybrid learning algorithm combining least-squares estimation and gradient descent, ANFIS successfully constructed input-output mappings from data while preserving the interpretability of fuzzy rules. The results demonstrated remarkable prediction accuracy in nonlinear function approximation and chaotic time-series forecasting, establishing ANFIS as a foundational model for intelligent prediction systems.

Jang and Sun (1995) extended neuro-fuzzy modeling concepts to control and prediction applications. Their work emphasized the ability of neuro-fuzzy systems to combine expert knowledge with data-driven learning. The authors argued that purely neural approaches often suffer from a lack of interpretability, whereas fuzzy systems require substantial expert intervention. By integrating these two paradigms, neuro-fuzzy models achieved both transparency and learning capability. Their findings demonstrated that neuro-fuzzy architectures are particularly effective in uncertain and dynamic environments where system behavior cannot be accurately represented using deterministic equations.

Ho et al. (2002) investigated the prediction of surface roughness in turning operations. The research addressed the difficulty of capturing the nonlinear relationship between machining parameters and product quality. ANFIS was employed to model the interaction among cutting speed, feed rate, and tool conditions. The experimental results revealed that the proposed model significantly outperformed conventional regression techniques in prediction accuracy. More importantly, the study demonstrated that ANFIS could effectively represent complex manufacturing phenomena while maintaining a transparent rule-based structure, making it highly suitable for industrial applications.

Chien, Wang, and Lin (2010) applied neuro-fuzzy networks to forecast innovation performance in manufacturing industries. The study examined the nonlinear relationships among technological resources, research activities, and innovation outcomes. By comparing ANFIS with traditional statistical models and neural networks, the authors found that neuro-fuzzy systems produced superior forecasting performance and generated interpretable decision rules. Their findings reinforced the suitability of ANFIS for modeling complex manufacturing environments characterized by uncertainty and multiple interacting variables.

Baseri and Belali-Owsia (2017) proposed a hybrid Imperialist Competitive Algorithm (ICA)–ANFIS model for manufacturing process performance prediction. The

study recognized that the effectiveness of ANFIS strongly depends on the selection of membership functions and fuzzy rules. To overcome this limitation, the ICA was employed to optimize ANFIS parameters. Experimental results demonstrated a substantial reduction in prediction errors compared with conventional ANFIS models. The authors concluded that hybridization strategies can significantly improve the robustness and generalization capability of neuro-fuzzy systems in manufacturing applications.

Azizi et al. (2011) addressed the challenge of predicting production throughput in manufacturing systems operating under uncertain conditions. Traditional deterministic forecasting methods often fail to capture the nonlinear relationships and uncertainty associated with production variables such as machine breakdowns, setup times, and operational disturbances. To overcome these limitations, the authors developed an ANFIS model capable of integrating fuzzy reasoning with neural network learning capabilities. A real industrial case study was used to train and validate the model using historical production data. The results demonstrated that ANFIS successfully captured the nonlinear dynamics of the production environment and generated accurate throughput predictions. The study concluded that ANFIS provides an effective decision-support tool for production managers dealing with uncertainty and variability in manufacturing systems.

Azizi et al. (2012) investigated the problem of modeling uncertain production-line variables in the ceramic tile industry, where operational performance is significantly influenced by stochastic and imprecise factors. The research aimed to compare the predictive capabilities of Bayesian inference and ANFIS approaches in handling uncertainty. Using production data collected from an industrial tile manufacturing facility, both models were developed and evaluated based on their prediction accuracy and adaptability. The comparative analysis revealed that ANFIS outperformed the Bayesian model in capturing nonlinear relationships and complex interactions among production variables. The findings indicated that ANFIS achieved lower prediction errors and greater flexibility under changing production conditions, making it a more suitable approach for industrial environments characterized by uncertainty and dynamic behavior.

Azizi et al. (2013) focused on the modeling of dynamic production systems where uncertainty continuously affects operational performance. The study highlighted the limitations of conventional analytical models in representing rapidly changing manufacturing conditions and emphasized the need for intelligent predictive systems. To address this issue, an ANFIS-based framework was developed to model production behavior under varying operational scenarios. The proposed model utilized historical production data and fuzzy membership functions to learn complex nonlinear patterns within the system. Experimental results showed that the ANFIS model accurately predicted production performance indicators despite fluctuations in input variables. The

authors concluded that the hybrid neuro-fuzzy approach provides a robust and adaptive mechanism for supporting decision-making in dynamic manufacturing environments and can enhance production planning effectiveness under uncertainty.

Azizi et al. (2015) examined the broader problem of uncertainty modeling in manufacturing systems and proposed an Adaptive Neuro-Fuzzy Inference System as an intelligent framework for representing uncertain production conditions. The study recognized that production performance is affected by multiple interrelated variables whose relationships are often nonlinear and difficult to model using conventional statistical techniques. The authors developed an ANFIS model to estimate production outcomes based on uncertain operational inputs and validated its performance using industrial manufacturing data. The results demonstrated high predictive accuracy and strong generalization capability, indicating that the model effectively captured hidden patterns within the production process. The research showed that ANFIS can serve as a reliable tool for uncertainty modeling, production forecasting, and operational decision support, thereby contributing to improved manufacturing performance and productivity management.

Schneckenreither et al. (2021) examined order-release planning with predictive lead times in manufacturing. They developed a machine-learning approach that uses an artificial neural network to estimate dynamic lead times rather than relying on fixed values. Their results showed that predictive lead times can improve order-release decisions and reduce planning inefficiencies relative to static lead-time assumptions.

Liu et al. (2022) studied dynamic scheduling in semiconductor manufacturing under uncertain processing times and urgent orders. They proposed a framework combining convolutional neural networks with deep reinforcement learning for integrated release control and production scheduling. Simulation results showed improved scheduling performance compared with conventional dispatching and baseline reinforcement-learning approaches under uncertain operating conditions.

Steinberg et al. (2022) studied assembly delay prediction in the automotive industry. The main issue was the uncertainty caused by material shortages and assembly process variations. The researchers used Random Forest and Gradient Boosting algorithms. The results showed that raw material information has a significant impact on the accuracy of delay prediction and machine learning models outperform statistical methods.

Bekci et al. (2022) investigated the problem of lead time prediction in laser manufacturing processes. Gaussian Process, Probabilistic Neural Networks, and Gradient Boosting were used to model uncertainty. The results showed that probabilistic approaches not only have higher accuracy than traditional estimates, but also provide the ability to provide confidence intervals for lead time.

Rohaninejad et al. (2023) studied the integrated batch size and scheduling problem considering demand and processing time uncertainty. The proposed model used machine learning to estimate safety parameters in the rescheduling process. The results showed that the proposed method increases the stability of the production schedule and reduces the delay caused by processing time changes.

Botelho et al. (2026) investigated the problem of predicting the remaining time of production orders. They presented a hybrid model including Process Mining and Machine Learning that extracted real process information from Event Log. The results showed that the hybrid model improves the accuracy of predicting the order completion time compared to the single models and is suitable for decision-making in production planning.

De Simone et al. (2026) addressed the problem of lead time forecasting in small and medium-sized enterprises. The proposed method was based on a digital masterplan system for collecting and analyzing production data. The results indicated that the proposed model was capable of providing lead time forecasting with high accuracy and had practical applicability in industrial environments.

Mutambik (2026) investigated the problem of lead time prediction in resilient supply chains. The research focused on the role of artificial intelligence in dealing with environmental changes and operational uncertainties. The results showed that the use of AI-based adaptive models can increase the accuracy of lead time prediction and improve supply chain resilience.

Meisheri et al. (2022) investigated the problem of stochastic lead time in multi-product systems. The proposed method was based on Reinforcement Learning, which had the ability to learn in environments with delays and uncertainty. The results showed that the proposed model is able to reduce the negative effects of lead time fluctuations and improve inventory performance.

Alves and Mateus (2022) investigated the production and distribution scheduling problem in a multilevel supply chain with stochastic lead time. The proposed model was developed based on Deep Reinforcement Learning and PPO algorithm. The results showed that in the conditions of high uncertainty, the deep learning approach provides better performance than the classical programming methods.

The literature review confirms that ANFIS is a powerful tool for modeling nonlinear and uncertain industrial systems. However, most previous research has focused either on prediction using standalone ANFIS models or on optimization-based hybridizations. Limited attention has been devoted to integrating fuzzy clustering with ANFIS for manufacturing lead-time prediction under simultaneous uncertainties arising from machine failures, bottleneck delays, setup-time variability, processing-time fluctuations, and work-in-process congestion. In the literature reviewed for this study, no single approach was identified that simultaneously combines these uncertainty sources within a hybrid FCM–ANFIS architecture for production lead-time prediction. The

proposed model addresses this gap by using fuzzy clustering to reduce operational-state heterogeneity before cluster-specific neuro-fuzzy learning.

3. RESEARCH METHODOLOGY

The research methodology follows a sequence that links data generation, data preparation, fuzzy clustering, cluster-specific ANFIS learning, and model validation (Figure 1). The purpose of this sequence is to separate heterogeneous production states before prediction and then evaluate whether this separation improves lead-time prediction.

Research Methodology Flowchart

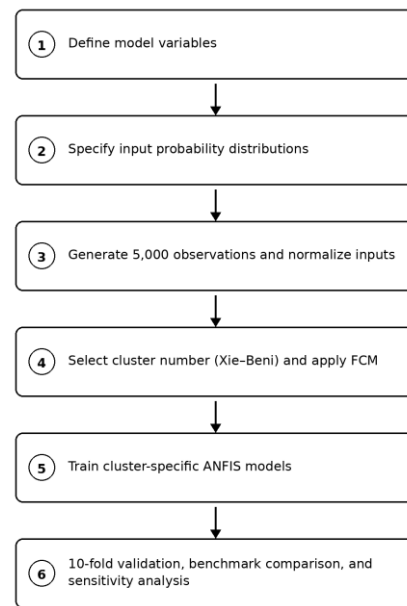


Figure 1. Research methodology flowchart

Conceptual Model of the Proposed FCM–ANFIS Approach

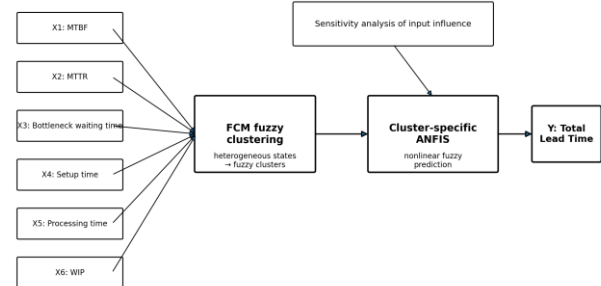


Figure 2. Conceptual model of the proposed FCM–ANFIS approach

The methodology comprises six main steps (Figure 2):

Step 1: Define the model variables

The six input variables are MTBF, MTTR, bottleneck waiting time, setup time, processing time, and WIP. Total production lead time (LT) is the response variable. The variables and their definitions are reported in Tables 1 and 2.

The input variables are given in Table 1.

Table 1. Model input variables

Variable	Symb ol	Definition
X1	MTB F	Mean time between failures
X2	MTT R	Mean time to repair
X3	BT	Bottleneck waiting time
X4	ST	Setup time
X5	PT	Processing time
X6	WIP	Work-in-process inventory

The output variable is presented in Table 2.

Table 2. Model output variable

Variable	Symb ol	Definition
Y	LT	Total production lead time

Step 2: Specify the probability distributions of the input variables

The distributions used to generate the simulation data are reported in Table 3.

Table 3. Distribution functions of input variables

Variable	Distribution function
X1	Exp($\lambda = 0.02$)
X2	N(4, 1.2)
X3	U(10, 35)
X4	N(50, 8)
X5	N(20, 5)
X6	U(100, 500)

Step 3: Generate the production lead-time observations

For each simulation run, the operating conditions are generated from the probability distributions reported in Table 3. The resulting production observations contain the specified variability in machine reliability, bottleneck waiting, setup time, processing time, and WIP. The total production lead time recorded by the simulation is used as the model output. The simulated lead-time response is generated according to the following relation:

$$LT = 0.35 PT + 0.25 BT + 0.15 ST + 0.20 MTTR + 0.05 WIP^{0.5} + \varepsilon$$

$$\varepsilon \sim N(0, 3)$$

Step 4: Fuzzy C-Means clustering

Before training ANFIS, the normalized observations are partitioned into fuzzy clusters. The number of clusters is selected using the Xie–Beni validity index. FCM assigns each observation a membership degree for each cluster rather than forcing it into a single hard group, allowing gradual transitions between production states.

FCM clustering formulation

$$J = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m \|x_i - c_j\|^2 \quad (1)$$

where:

u_{ij} : fuzzy membership degree of observation i in cluster j

c_j : center of cluster j

The fuzzifier parameter is set to $m = 2$.

The cluster centers and fuzzy memberships are updated iteratively using:

$$c_j = \frac{\sum_i u_{ij}^m x_i}{\sum_i u_{ij}^m} \quad (2)$$

$$u_{ij} = \frac{1}{\sum_k \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (3)$$

Step 5: Cluster-specific ANFIS models

A Takagi–Sugeno ANFIS model is trained for each identified production cluster. The model uses the input variables in Table 1 and learns nonlinear input–output relationships through fuzzy rules and data-driven parameter adjustment. The final lead-time prediction is obtained from the cluster-specific inference process.

ANFIS formulation

Takagi–Sugeno rules are written for each cluster.

Rule 1: If MTTR = Low $\wedge$ BT = Low, then $f_1 = a_1 X_1 + b_1 X_2 + \dots + r_1$

Rule 2: If MTTR = High $\wedge$ BT = High, then $f_2 = a_2 X_1 + b_2 X_2 + \dots + r_2$

Step 6: Model validation and comparison

The complete validation and comparison procedure is implemented in the following order:

1. Generate 5,000 simulation observations.
2. Normalize the input variables.
3. Determine the appropriate number of clusters using the Xie–Beni index.
4. Apply FCM and obtain fuzzy memberships.
5. Train a separate ANFIS model for each cluster.
6. Evaluate the models using 10-fold cross-validation.
7. Compare FCM–ANFIS with linear regression, ANN, random forest, XGBoost, and standalone ANFIS.
8. Conduct sensitivity analysis to identify the input variables that contribute most strongly to lead-time variation.

4. RESULTS

The correlation analysis indicated no excessively strong pairwise association among the input variables. The Variance Inflation Factor (VIF) values were within the commonly accepted range, indicating that severe multicollinearity was not present. The nonlinear dependency analysis also did not reveal substantial redundant information among the predictors. Therefore,

the six input variables (MTBF, MTTR, BWT, ST, PT, and WIP) were retained as distinct predictors for the FCM–ANFIS model.

The FCM–ANFIS model produced the lowest prediction error across all three evaluation criteria. Its RMSE, MAE, and MAPE were 2.84 hours, 2.11 hours, and 4.37%, respectively. Compared with the standalone ANFIS model, the proposed approach reduced RMSE by approximately 22.6%, indicating that fuzzy clustering improved prediction accuracy under the heterogeneous operating conditions represented in the simulation. Linear regression produced the largest errors among the benchmark models.

The comparative prediction results are given in Table 4.

Table 4. Comparative prediction results

Model	RMSE	MAE	MAPE
Linear Regression	7.89	6.11	12.8%
ANN	5.72	4.45	8.4%
Random Forest	4.93	3.87	7.1%
XGBoost	4.28	3.24	5.8%
ANFIS	3.67	2.96	5.1%
FCM–ANFIS	2.84	2.11	4.37%

4.1. Sensitivity Analysis

The sensitivity index is formulated as follows:

$$SI_i = \frac{\Delta LT / LT}{\Delta X_i / X_i} \quad (4)$$

The results of the sensitivity analysis are given in Table 5.

Table 5. Sensitivity analysis results

Factor	Sensitivity	Effect on lead time
MTTR	0.34	Positive
Bottleneck waiting time	0.29	Positive
Processing time	0.18	Positive
Setup time	0.11	Positive
WIP	0.08	Positive
MTBF	-0.13	Negative

A 1% increase in MTBF reduces production lead time by approximately 0.13%, whereas a 1% increase in MTTR increases lead time by approximately 0.34%.

5. DISCUSSION

The primary objective of this study was to develop an intelligent prediction model capable of estimating production lead time under multiple simultaneous uncertainty sources, including machine breakdowns, stochastic bottleneck delays, setup time variability, processing time fluctuations, and work-in-process congestion. The experimental results demonstrate that the proposed hybrid FCM–ANFIS model outperforms the benchmark prediction approaches, including multiple linear regression, artificial neural networks, random forest, XGBoost, and standalone ANFIS models. The

superior performance of the proposed model can be attributed to the synergistic integration of fuzzy clustering and neuro-fuzzy learning. Manufacturing environments are inherently heterogeneous and exhibit different operational states caused by varying production loads, machine conditions, and bottleneck behaviors. By partitioning the dataset into homogeneous fuzzy clusters, the FCM algorithm successfully reduces data dispersion and captures hidden production patterns before the learning phase. Consequently, the ANFIS model can construct more accurate local inference rules and better approximate nonlinear relationships among production variables. The findings are consistent with previous studies emphasizing the importance of machine learning for lead-time prediction. For example, Schneckeneither et al. reported that machine learning-based lead-time estimation significantly improves production planning performance compared with traditional planning methods. Similarly, Bekci et al. demonstrated that probabilistic machine learning models outperform conventional estimation techniques in manufacturing lead-time prediction. Furthermore, the obtained results support the observations of Steinberg et al., who highlighted that incorporating additional operational information substantially improves prediction accuracy in manufacturing environments. The present study extends this perspective by integrating machine reliability indicators, bottleneck waiting times, setup times, and processing times within a unified prediction architecture. The sensitivity analysis revealed that MTTR and bottleneck waiting time are the most influential factors affecting production lead time. This finding is theoretically justified because machine failures directly interrupt production flow, while bottlenecks propagate delays throughout downstream operations. Similar conclusions have been reported in bottleneck prediction studies, where bottleneck dynamics were identified as dominant determinants of cycle time and throughput performance.

Another important observation is the capability of the proposed model to model nonlinear interactions among uncertainty sources. Traditional regression models assume linear relationships and therefore cannot adequately capture the complex dependencies between machine failures, setup operations, and processing activities. Although ANN and XGBoost demonstrated relatively strong predictive performance, they do not provide the same rule-based inference structure as ANFIS. The proposed FCM–ANFIS model combines high predictive accuracy with a neuro-fuzzy inference structure that can support more transparent managerial interpretation.

From an Industry 4.0 perspective, the proposed approach can serve as a practical component of intelligent production control systems. The model can continuously receive operational data from Manufacturing Execution Systems (MES), predict future lead times, and support dynamic scheduling decisions under uncertainty. Therefore, the model contributes not only to predictive

analytics but also to resilient and adaptive manufacturing management.

6. CONCLUSION

This study proposed a novel hybrid Fuzzy C-Means Adaptive Neuro-Fuzzy Inference System (FCM–ANFIS) model for manufacturing lead-time prediction under multiple operational uncertainties. Unlike previous studies that focused on isolated uncertainty factors or relied solely on conventional machine learning algorithms, the proposed model simultaneously considered machine breakdowns, stochastic bottleneck delays, setup time variability, processing time uncertainty, and work-in-process fluctuations. A simulation-based manufacturing environment was developed to generate controlled production data and evaluate the predictive capability of the proposed model. Experimental results demonstrated that the hybrid FCM–ANFIS model achieved the highest prediction accuracy among all benchmark models. The results confirmed that fuzzy clustering effectively reduces data heterogeneity, while neuro-fuzzy learning accurately captures complex nonlinear relationships within production systems. The sensitivity analysis further revealed that machine repair duration and bottleneck waiting time are the most critical determinants of production lead time. These findings provide valuable managerial insights for prioritizing maintenance activities, improving bottleneck

management, and enhancing production scheduling policies. From a theoretical standpoint, this study contributes to the growing body of intelligent manufacturing literature by integrating fuzzy clustering and neuro-fuzzy inference into a unified lead-time prediction architecture. From a practical perspective, the proposed model offers a reliable decision-support tool for production planners seeking improved delivery performance, scheduling accuracy, and operational resilience in Industry 4.0 environments.

Despite its promising results, the study has several limitations. First, the experiments were conducted using simulated manufacturing data rather than real industrial datasets. Second, only a single production configuration was considered. Future research may validate the proposed model using real-world manufacturing datasets collected from automotive, semiconductor, pharmaceutical, and process industries. Additionally, future studies may integrate digital twin technologies, deep learning architectures such as LSTM and Transformer networks, and explainable artificial intelligence techniques to further enhance prediction accuracy and interpretability.

Overall, the findings demonstrate that the proposed FCM–ANFIS model provides an effective predictive solution for manufacturing lead-time prediction in highly uncertain production environments and represents a promising direction for next-generation intelligent production planning systems.

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