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Assessing the Impact of Disturbance Factors on Manufacturing Enterprise Scheduling

Mayur Qumer Collins[1] and Estrella Galbraith[2]

[1,2]Western Sydney University, Rydalmere, Australia
[1]mayur.collins@westernsydney.edu.au, [2]e.galbraith@westernsydney.edu.au

Abstract

This research paper investigates the impact of various disturbance factors on manufacturing enterprise scheduling. Factors such as machine breakdowns, supply chain interruptions, and fluctuating customer demands can significantly disrupt production schedules and reduce operational efficiency. To address these issues, this study systematically describes and classifies disturbance factors based on their specific impacts and characteristics. Given the complex and often uncertain nature of these disturbances, a novel approach utilizing a fuzzy neural network is proposed to assess and mitigate their effects. This method aims to improve the accuracy and adaptability of scheduling decisions, thereby enhancing the resilience and efficiency of production processes. Through simulation experiments with real-world scenarios, the proposed approach's effectiveness is validated, demonstrating notable improvements in schedule reliability and overall operational performance. The findings underscore the potential of fuzzy neural networks in providing robust solutions for managing uncertainty in manufacturing scheduling, offering valuable insights for both practitioners and researchers in the field.

Keywords: *Disturbance factors, Manufacturing enterprise scheduling, Fuzzy neural network*

1. Introduction

Manufacturing enterprises face numerous challenges in maintaining efficient and reliable production schedules due to various disturbance factors. These disturbances, including machine breakdowns, supply chain interruptions, and fluctuating customer demands, can significantly disrupt operations and lead to inefficiencies. Addressing these challenges requires a comprehensive understanding and effective management of disturbance factors to enhance production scheduling and overall operational performance.

Recent research has extensively explored the identification and mitigation of disturbance factors in manufacturing systems. Shi et al. [1] employed probability theory and mathematical statistics to quantify disturbance levels, providing a foundation for systematic analysis. Shan [2] categorized disturbance factors into dominant and recessive classes based on their impact on the production system, highlighting the importance of tailored response strategies. Heidergott and Bernd [3] introduced a finite perturbation analysis method (CFPA) that incorporates customer feedback to establish a robust perturbation analysis model. Similarly, Abell et al. [4] leveraged simulation and a perturbation analysis (CSPA) algorithm to

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implement perturbation analysis technology within an object-oriented production system framework.

Despite these advancements, more research is still needed to focus on the degree of disturbance within the system and its direct impact on scheduling accuracy. Current studies have predominantly concentrated on identifying disturbance factors and proposing general solutions. However, a targeted approach to determine the specific degree of disturbance factors that influence production schedules is essential for developing resilient and adaptive scheduling methods.

This study aims to bridge this gap by introducing a novel approach that utilizes a fuzzy neural network algorithm to evaluate and mitigate the effects of disturbance factors on manufacturing enterprise scheduling. First, we classify common disturbance factors into three categories: Type A, Type B, and Type C. We then focus on Type B disturbance factors, using the fuzzy neural network algorithm to assess their impact and optimize scheduling decisions. Finally, the proposed method's effectiveness is validated through simulation experiments, demonstrating significant improvements in schedule reliability and overall operational performance.

2. Literature Review

The study of disturbance factors in manufacturing enterprise scheduling has gained significant attention over recent years, driven by the need to enhance operational efficiency and reliability. This literature review examines key contributions to the field, focusing on the identification, classification, and mitigation of disturbance factors through various analytical and computational approaches.

(1) Identification and Classification of Disturbance Factors

Several scholars have contributed to the identification and classification of disturbance factors in manufacturing systems. Shi et al. [5] utilized probability theory and mathematical statistics to quantify disturbance levels, providing a framework for systematic analysis of disruptions. Shan [2] extended this work by categorizing disturbance factors into dominant and recessive classes based on their impact on production systems, which allowed for more tailored response strategies. This classification has been pivotal in understanding the nature and severity of various disturbance factors, guiding subsequent mitigation efforts.

(2) Perturbation Analysis and Simulation

Perturbation analysis has emerged as a critical tool for assessing and managing disturbances in manufacturing scheduling. Heidergott and Bernd [3] introduced a finite perturbation analysis (CFPA) method that incorporated customer feedback, establishing a robust model for evaluating the effects of disturbances on production schedules. Abell et al. [4] leveraged simulation and a perturbation analysis (CSPA) algorithm to implement perturbation analysis technology within an object-oriented production system framework, demonstrating the utility of simulation in predicting and mitigating disruptions.

(3) Computational Approaches

The application of computational approaches, particularly artificial intelligence and machine learning, has shown promise in addressing disturbance factors in manufacturing scheduling. Zhang et al. [6] explored the use of genetic algorithms to optimize scheduling under uncertain conditions, highlighting the adaptability of these algorithms to dynamic environments. Similarly, Lee et al. [7] proposed a reinforcement learning approach to real-time scheduling, which improved responsiveness and efficiency in the face of disturbances.

(4) Fuzzy Neural Networks

Fuzzy neural networks have been identified as a particularly effective tool for handling the complexity and uncertainty inherent in disturbance factors. Wang et al. [8] utilized fuzzy logic combined with neural networks to create adaptive scheduling systems that can learn and adjust to varying disturbance patterns. This approach has been shown to enhance the robustness and flexibility of production schedules, providing a significant advancement in the field.

(5) Recent Advances and Gaps

Despite these advancements, more research is still needed, particularly concerning the degree of disturbance within the system and its direct impact on scheduling accuracy. Current studies have predominantly focused on identifying disturbance factors and proposing general solutions, with less emphasis on targeted approaches to determine the specific influence of these factors on production schedules [8][9][10][11].

This study aims to address this gap by introducing a fuzzy neural network algorithm to evaluate and mitigate the effects of disturbance factors on manufacturing enterprise scheduling. By focusing on Type B disturbance factors, the research seeks to optimize scheduling decisions and enhance operational performance through a novel computational approach.

The existing literature provides a strong foundation for understanding and addressing disturbance factors in manufacturing scheduling. However, the need for more targeted and adaptive solutions remains evident. This study contributes to the field by proposing a fuzzy neural network approach, validated through simulation, to improve scheduling reliability and efficiency in the face of disturbances.

3. The judgment of fuzzy neural network based on fuzzy neural network

According to the degree of the disturbance factor, the common disturbance in the manufacturing workshop is divided into A-type, B-type, and C-type disturbance factors. The A-type disturbance factor needs to be carried out during the overall revision of the original plan. The B-type disturbance factor, which has the characteristic of fuzziness, needs to be analyzed according to the actual situation. As for the C-type disturbance factor, we need to use the periodic type weight scheduling strategy to eliminate its impact on the production system.

Because there are so many multiple fuzzy parameters in the B-type disturbance to influence the disturbance degree of the production system, at the same time, these fuzzy parameters and the output value of the degree of disturbance have complex nonlinear relations, it is difficult to establish a suitable function expression. In this paper, we propose a fuzzy neural network model [Figure 1] to evaluate the degree of disturbance of the B-type disturbance factor in the production system.

We use the fuzzy neural network to dispose of the B-type disturbance factor, including the parameter model and the neural network training two modules. The parameters of the model are to deal with the original data of all kinds of parameters that affect the disturbance degree of the production system in the B model, obtain the corresponding membership degree, and the results as the input of the neural network are normalized to the range of [0, 1]; The neural network training module is a nonlinear mapping relationship between the input parameters and the degree of disturbance.

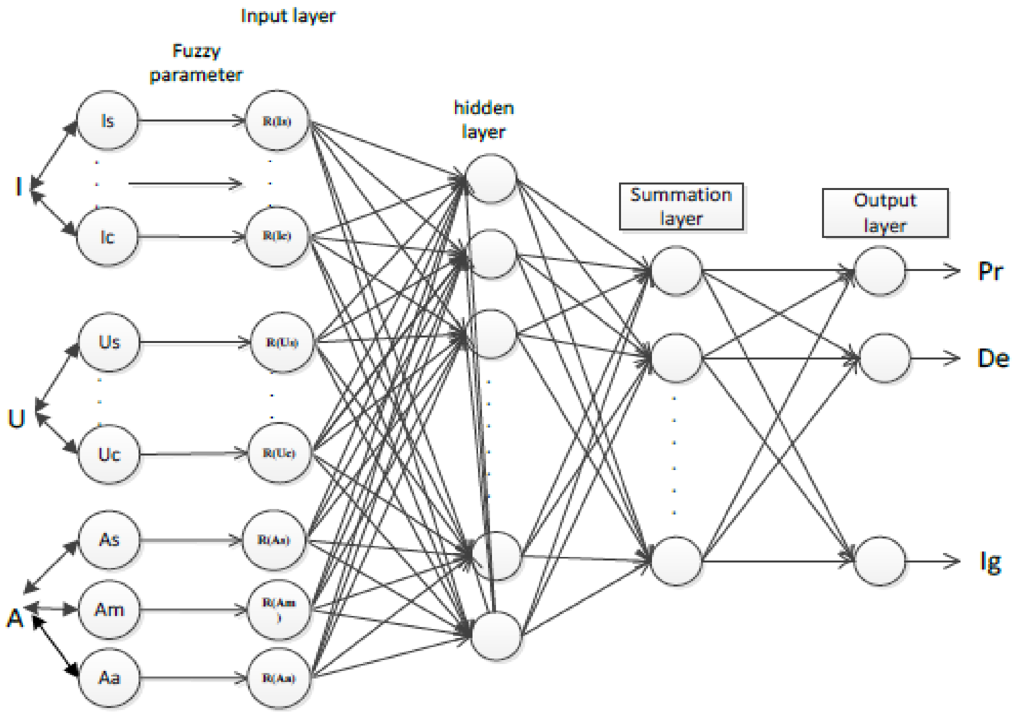

Figure 1. Fuzzy neural network model

1) Parameter fuzzy quantization

We define the disturbance degree of the B-type perturbation factor to the production system as δ, and the main parameters of the model are the following 3 types:

Intensity of disturbance I: This parameter is fuzzy. Fuzzy subset *T(I)={Is,Iw,Im,Ia,Ic}*, *Is,Iw,Im,Ia,Ic* stand for respectively the Intensity of the disturbance factor is mild, weak, moderate, strong and serious in this Set. The evaluation basis is affected by the number of processing steps, which uses the relative number of process nr to assess. As shown in the formula $n_r = n_a / N$. In this formula, *N* represents the number of the total number of processing operations in the scheduling optimization set, *and* n_a indicates that the number of processing steps affected by the optimization set is affected by the disturbance factors.

Emergency degree of disturbance factors U: This parameter is also fuzzy, Fuzzy subset *U(I)={Us,Uw,Um,Ua,Uc}. Us,Uw,Um,Ua, and Uc* stand for, respectively, the level of the disturbance factor is mild, weak, moderate, strong, and serious. The decision is based on the relative priority of the working procedure, which is affected by the disturbance factor. As shown in the formula $P_m =(\sum_{i=1}^{na} P_i /n_a)/P_{max}$. In this formula, P_m is the proportion of the highest priority in the process of the machining process, which is affected by the disturbance factor, na indicates that the total number of processing steps affected by the scheduling optimization set is affected by the disturbance factors. The P_i is the priority of the process operation in the scheduling optimization set, P_{max} is the priority of the scheduling optimization set. The Pm is divided into [0,1], *Us,Uw,Um,Ua,Uc* are taken as the type *R(x)*, and the corresponding membership degree is obtained.

Cumulative Intensity of disturbance factors A: This parameter has the *Aw, Am, Aa*. The 3 represents the fuzzy subset of the cumulative Intensity of the disturbance factor, Specific for T *(A) ={Aw, Am, Aa}*. Among them, *Aw, Am, and Aa* stand for, respectively, the cumulative degree of the disturbance factor is low, moderate, and high, and it describes the cumulative number of processing steps that are not affected by the various disturbance factors. The parameters are evaluated by the relative amount of n_{ar} in the process of accumulation, As shown in the formula $n_{ar} = n_{aa} / N$. In the formula, n_{aa} indicates that the number of the total number of the total number of processing operations is not affected by the disturbance factors, and the n_{aa} is the total number of processing operations. N represents the total number of processing operations for the scheduling optimization set. The n_{ar} is divided into [0,1], *Aw, Am,* and Aa, which is taken as the type *R(x)* and gets the corresponding membership degree.

2) Neural network

Because the second part of the quantitative analysis of the disturbance factor is based on the fuzzy neural network part of the neural network, we choose the probabilistic neural network to analyze the B-type disturbance factor. As shown in [Figure 1], the probabilistic neural network consists of four layers, which are the input layer, hidden layer, layer, and output layer. We choose 3 main parameters as the input of the neural network. The 3 main parameters are Intensity of disturbance Ig, emergency degree of disturbance factors U, and cumulative Intensity of disturbance factors A. Setting the Pr, De, and Ig of these three kinds of B-type disturbance factors to trigger the rescheduling request as the output of the neural network, which Pr said that the immediate implementation of the request, De said that the delay in the rescheduling request, Ig can be ignored. At the same time, the output value is as follows: the acceptance of the rescheduling request is 1, and the acceptance of the rescheduling request is 0.

4. Numerical example analysis and simulation

In this paper, we use the Matlab2012b version of the proposed fuzzy neural network algorithm to simulate. As follows: at first, we can generate 6 kinds of B-type disturbance factors and then set up the corresponding data of 6 kinds of disturbance factors. After getting data generation, we calculate the membership degree of fuzzy sets as the input of the neural network, according to the method of the fuzzy parameter. At the same time, for the input data, the experts in the field of relevant production scheduling judge their response strategies based on previous experience. That is, Pr, De, and Ig are the 3 kinds of heavy scheduling requests, which will select one of the 3 as a neural network output.

According to the above method, 150 cases are generated, 120 cases are randomly selected as training samples, and 30 cases are taken as test samples. [Table 1] is a training sample data.

Table 1. Partial training sample data

Input data							Expected output		
Type of B type disturbance factor	Occurrence intensity		Emergency degree		Cumulative Intensity		Pr	De	Ig
	The absolute number of affected processes	Relative number of affected processes	Affected highest priority processes.	Affected process's average priority	Affected the absolute cumulative number of processes	Affected the absolute cumulative number of processes			
C1	18	0.05	5	2.7	0	0	1	0	0
C1	20	0.06	4	3.0	12	0.05	0	1	0
C2	22	0.12	4	2.1	8	0.04	0	1	0
C2	20	0.17	4	2.9	17	0.05	1	0	0
C3	10	0.09	5	4.3	0	0	1	0	0
C3	18	0.13	4	3.2	6	0.07	0	1	0
C4	14	0.09	4	2.7	0	0	0	1	0
C4	30	0.38	4	3.2	11	0.05	1	0	0
···	···	···	···	···	···	···	···	···	···

Comparing the expected output and the actual output in [Table 2], we can get satisfactory results in the vast majority of cases when using the fuzzy neural network algorithm to solve the influence degree of B-type disturbance factor on the production system; that is to say, the validity of this method is verified.

Table 2. Partial test sample data

Input data							Actual output			Expected d output		
Type of B-type disturba nce factor	Occurrence intensity		Emergency degree		Cumulative Intensity		Pr	De	Ig	Pr	De	Ig
	The absolute number of affected processes	The relative number of affected processes	Affected highest priority process s	Affected process's average priority	Affected the absolute cumulative number of processes	Affected the absolute cumulative number of processes						
C1	20	0.08	5	2.9	6	0.07	1	0	0	1	0	0
C1	7	0.08	5	2.9	0	0	1	0	0	0	1	0
C1	20	0.19	4	3.2	24	0.22	1	0	0	1	0	0
C2	18	0.12	4	3.2	12	0.06	1	0	0	1	0	0
C2	3	0.03	4	3.9	0	0	0	1	0	0	1	0
C2	9	0.09	4	2.1	12	0.11	0	1	0	0	1	0
C2	3	0.03	4	2.9	4	0.03	0	1	0	0	1	0
C3	3	0.03	4	2.7	0	0	0	0	1	0	0	1
C3	8	0.08	5	3.3	0	0	1	0	0	1	0	0
C4	37	0.37	4	2.9	6	0.07	1	0	0	1	0	0
C4	22	0.22	4	3.2	14	0.06	1	0	0	1	0	0
C4	7	0.07	4	2.7	0	0	0	1	0	0	1	0
•••	•••	•••	•••	•••	•••	•••	•	•	•	•	•	•

5. Conclusions

This research has explored the significant impact of disturbance factors on manufacturing enterprise scheduling and proposed a novel approach using fuzzy neural networks to address these challenges. Disturbance factors such as machine breakdowns, supply chain interruptions, and fluctuating customer demands can severely disrupt production schedules and compromise operational efficiency. The study systematically classified these factors into three categories—Type A, Type B, and Type C—to facilitate targeted analysis and response.

Our research focused particularly on Type B disturbance factors, leveraging a fuzzy neural network algorithm to evaluate their impact and optimize scheduling decisions. The results from simulation experiments, based on real-world scenarios, validate the effectiveness of this approach, demonstrating significant improvements in schedule reliability and overall operational performance. The fuzzy neural network's ability to handle complexity and uncertainty has proven to be a robust solution for enhancing the adaptability and resilience of manufacturing schedules.

The findings underscore the potential of integrating advanced computational techniques, such as fuzzy neural networks, into manufacturing scheduling systems. This approach not only improves the accuracy and responsiveness of scheduling decisions but also contributes to the development of more resilient production processes capable of withstanding various disturbances.

While this study has made substantial contributions to the field, there are opportunities for further research. Future studies could explore the integration of other machine learning algorithms with fuzzy logic to enhance the robustness of scheduling systems further. Additionally, expanding the scope to include a broader range of disturbance factors and their interactions would provide deeper insights into managing uncertainties in manufacturing.

In conclusion, this research highlights the critical importance of addressing disturbance factors in manufacturing scheduling. It presents a promising methodology for practitioners and researchers aiming to improve operational efficiency and reliability. By continuing to develop and refine these techniques, the manufacturing industry can better navigate the complexities and uncertainties inherent in production environments.

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