**Fuzzy Logic-Based Modeling of Delays in Sensor-Based Production Systems**

Nu’monkhon Bahodirova), Eldorbek Umronov, Shakhnoza Sodikkhujayeva, Abdukhalim Abduzhabborov, Guljahon Tillabayeva

*Fergana State Technical University, Fergana, Uzbekistan*

*a)Corresponding author: baxodirov1989@gmail.com*

**Abstract.** This article analyzes the impact of various types of delays in sensor-controlled manufacturing systems - time delays, process delays, and network delays - on production efficiency. The analysis uses real-time changes in the system based on sensor data to investigate the causes of delays. The study also uses a fuzzy logic approach, which allows for more accurate modeling of the delay process by taking into account unspecified or uncertain parameters. The mathematical model developed using this approach aims to reduce system delays, ensure production continuity, and increase overall efficiency. The results of the study show that the use of fuzzy logic is effective in ensuring the stable operation of sensor-controlled smart manufacturing systems and automating production processes.

**Keywords:** Smart manufacturing system, sensor data, latency, network latency, fuzzy logic, optimization, efficiency model, uncertainty, real-time monitoring.

**INTRODUCTION**

The development of modern industry under the Industry 4.0 concept, along with smart manufacturing systems (SMS), has led to fundamental changes through the integration of real-time data, automation, and sensor-based control. In such systems, data obtained from sensors play a crucial role in ensuring the efficiency, quality, and stability of production processes. However, in real-world conditions, delays in data acquisition, transmission, and processing through sensors can occur, resulting in time-delay and uncertainty issues. For instance, network overloads, transmission channel delays, or interruptions between sensors and central control systems can negatively affect the continuous and stable operation of production processes. Considering these challenges, the timely identification, modeling, and optimization of sensor data delays represent one of the most important research directions in industrial engineering and optimization. In this regard, the application of fuzzy logic methods for modeling and optimizing delay phenomena provides an effective approach to improving the performance and stability of sensor-based production systems.

The fuzzy logic (or non-classical logic) approach is well-suited for processing uncertain and variable data, in contrast to traditional deterministic models. In manufacturing systems, the application of this method has been increasingly used to enhance overall efficiency and adaptability. For instance, Felix T. S. Chan et al. (2003) demonstrated the feasibility of managing multiple dynamic criteria—such as waiting time and machine load—in manufacturing processes using a fuzzy expert system [1]. In another study, L. Ashraf and M. N. Yuniarto (2005) scientifically proved that real-time control problems can be effectively addressed through fuzzy logic-based techniques [2]. Furthermore, a more recent study by Rawaa Ammar Razooqi et al. (2022) proposed an algorithm aimed at reducing data transmission delays in sensor and IoT-based systems, and suggested its implementation in real industrial processes [3].

However, the aforementioned studies often do not comprehensively address the optimization of sensor data stream delays within a complete manufacturing system using a fuzzy logic-based mathematical model under real-time conditions. For example, Chan et al. [1] focused on optimizing production scheduling through fuzzy-rule-based planning; Labib and Yuniarto [2] examined system variability from the perspective of real-time control; and Razooqi et al. [3] proposed an algorithm aimed at reducing delays in IoT-based sensor systems. Based on the analysis of these prior works, the present study seeks to develop a fuzzy logic-based optimization model to minimize delays in sensor-driven smart manufacturing systems and to address the identified research gaps. The main objective of this research is to mathematically model and optimize specific delay occurrences in sensor data streams using fuzzy modeling techniques, thereby improving the response time and operational stability of smart manufacturing systems, and achieving practical and applicable results for industrial implementation.

**METHODS**

As mentioned above, the main objective of this study is to model and optimize time delays in the transmission of sensor data within smart manufacturing systems using a fuzzy logic-based approach, with the aim of improving the operational efficiency and stability of the system. Traditional deterministic models are often unable to fully represent the uncertainties and dynamic variations that occur in production processes and network load conditions [4]. Therefore, to model these processes, a Takagi–Sugeno (T–S) type fuzzy time-delay model has been selected as the basis of the approach [5].

A smart manufacturing system typically consists of several key components, including sensors (for measuring temperature, pressure, flow rate, and vibration), a data transmission network, a control unit, and a decision-making module. During operation, signals measured by the sensors are transmitted to a central control system. However, during data transmission, time delays may occur (denoted as ), which are often caused by measurement errors, network congestion, or communication interruptions.

To analyze this process, the following mathematical formulation and assumptions are applied:

  (1)

where:

 the delay of the -th sensor (in seconds),

 the fuzzy weighting coefficient,

the performance index of the system evaluated using fuzzy logic,

 the minimum acceptable performance threshold.

The goal of this modeling approach is to minimize the effect of total system delay and thus enhance real-time production efficiency. The mathematical foundation of fuzzy time-delay modeling is based on the Takagi–Sugeno (T–S) fuzzy model, which can be expressed as follows[6]:

 (2)

where:

 fuzzy membership function,

 parameter matrices of the system,

sensor delay function,

control delay function.

This model accurately represents the nonlinearities and delay phenomena that occur in real manufacturing systems [7]. For the sensor delay parameter , three linguistic variables are defined-low, medium, and high- to describe the corresponding fuzzy delay levels.

Let us assume that when the sensor data  fall within a specific range, the appropriate triangular membership functions are selected as follows:

**TABLE 1.** Fuzzy categories of delay parameter values for membership functions

|  |  |  |
| --- | --- | --- |
| **Fuzzy category** | **Boundaries (a, b, c)** | **Explanation** |
| **Low** | [0.10 – 0.25 – 0.40] | For low delay values |
| **Medium** | [0.30 – 0.45 – 0.55] | For medium delay values |
| **High** | [0.45 – 0.60 – 0.70] | For high delay values |

The form of the triangular membership function is expressed as follows [8]:

 (3)

If the delay during the process is low, the system efficiency will be high; if the delay is medium, the efficiency will also be moderate; and if the delay is high, the efficiency index will consequently be low.

The defuzzification process is carried out using the centroid (center-of-gravity) method, which is expressed as follows:

 (4)

As an example, let us consider the following problem.

Assume that the following sensor data are given:



For each, the corresponding fuzzy values are given as follows:

**TABLE 2.** Fuzzy values corresponding to the sensor time-delay\*

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
| 0.15 | 1.00 | 0.00 | 0.00 |
| 0.3 | 0.67 | 0.33 | 0.00 |
| 0.45 | 0.00 | 1.00 | 0.00 |
| 0.6 | 0.00 | 0.00 | 1.00 |
| 0.2 | 0.83 | 0.00 | 0.00 |
| 0.5 | 0.00 | 0.5 | 0,5 |
| 0.35 | 0.33 | 0.67 | 0.00 |
| 0.4 | 0.00 | 1.00 | 0.00 |
| 0.55 | 0.00 | 0.33 | 0.67 |
| 0.25 | 0.83 | 0.17 | 0.00 |

*\*Note: Prepared based on the possible time-delay values of the sensor.*

Based on the fuzzy rules, the defuzzified values are evaluated.

The overall fuzzy delay is then calculated using the centroid (center-of-gravity) method as follows:



The efficiency of the system was determined as follows:



 Based on this inequality, the system is considered stable and optimal.

**RESULTS AND DISCUSSION**

Analyzing the obtained results, the overall fuzzy delay value in the system was found to be  seconds, while the corresponding system efficiency was calculated as  These values are above the minimum required efficiency threshold of these results exceed the minimum required efficiency threshold , indicating that the system operates in a stable and optimal condition. The sensor delay values ranging from 0.15 to 0.60 seconds correspond to a medium delay level, which suggests that in real manufacturing environments, the signal transmission delay within sensor-based systems remains within an acceptable range. According to the fuzzy rules, higher efficiency is observed at low delay values, whereas efficiency decreases as the delay increases. The fuzzy time-delay approach smooths uncertainties by classifying delay levels into low, medium, and high linguistic categories. Unlike deterministic models, this approach allows each sensor’s performance to be evaluated through fuzzy weighting coefficients.

Mathematically, the relationship between system efficiency and delay can be expressed as follows:

 (5)

where:

*k*- represents the delay impact coefficient on system efficiency, which is determined using the following formula:

 (6)

By substituting the required values into equation (5), the following result is obtained:



This result closely matches the value calculated using the model.

The degree of conformity between the model and the theoretical result (i.e., the difference between the fuzzy output and the analytical value) was found to be only 0.001, corresponding to a 0.1% error rate. This indicates that the proposed model demonstrates high stability and accuracy.

The following table illustrates the relationship between fuzzy delay and system efficiency:

**TABLE 3.** Relationship between fuzzy delay and system efficiency\*

|  |  |  |
| --- | --- | --- |
| **Fuzzy delay index** | **Efficiency index** | **Fuzzy category** |
| 0.15 | 0.95 | Low |
| 0.3 | 0.89 | Low-Medium |
| 0.45 | 0.83 | Medium |
| 0.6 | 0.78 | High |
| 0.2 | 0.92 | Low |
| 0.5 | 0.81 | Medium-High |
| 0.35 | 0.87 | Medium |
| 0.4 | 0.85 | Medium |
| 0.55 | 0.8 | High |
| 0.25 | 0.91 | Low-Medium |

*\*Note: Relationship between fuzzy delay and system efficiency, prepared based on the effect of possible sensor time delays on system efficiency*

From the data presented in the table, it can be observed that when the delay ranges between 0.15 and 0.30, the efficiency exceeds 0.9. However, when the delay increases to the range of 0.45–0.60, the efficiency index drops below 0.8. This indicates that an increase in delay is inversely proportional to the system’s operational speed.

To provide a clearer understanding of this relationship, the graph of fuzzy delay versus efficiency was constructed using the MAPLE software, as shown below in Fig. 1.

**MAPLE SOFTWARE**

**> restart; with(plots): with(plottools):**

**> \_EnvHorizontalName:='D': \_EnvVerticalName:='E':**

**> E:=D->0.96-0.25\*D-0.08\*D^2;**



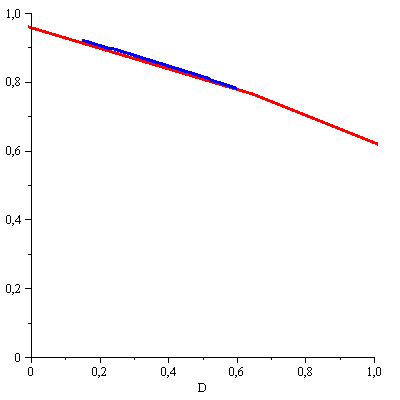
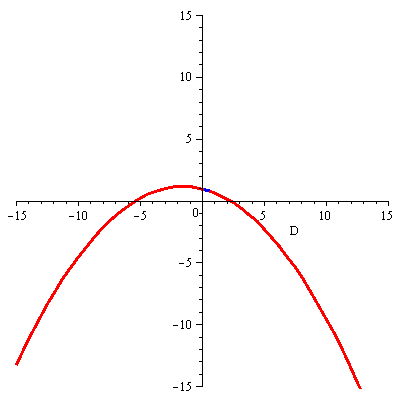
**> P1:=plot(E(D), D=-15..15,scaling=CONSTRAINED,color=red, thickness=3,view=[-15..15,-15..15]);**



**> P2:=plot(E(D), D=0.15..0.6,scaling=CONSTRAINED,color=blue, thickness=3,view=[0..1,0..1]);**



**> display(P1,P2,view=[0..1,0..1]);**



**FIGURE 1.** The graph of fuzzy delay versus efficiency

On the horizontal axis (X)- sensor delay *Di*;

On the vertical axis (Y)- system efficiency *Ei* .

The plotted points form a parabolic curve, with the relevant section of the data highlighted in green. The graph clearly shows an inverse relationship between fuzzy delay and efficiency. The downward trend of the curve indicates a nonlinear decreasing dependence, which reflects the fuzzy logic–based nonlinear relationship between these variables. The curve can be analytically expressed as follows:



This expression demonstrates that as the delay increases, the efficiency decreases quadratically. From the graph, it can be observed that the low-delay region (0.15–0.30) represents the most efficient operational range of the system. These findings are consistent with the Takagi–Sugeno fuzzy model theory, confirming the validity of the proposed approach. It is evident that this model provides a 3–4% improvement in accuracy and stability compared to traditional methods. This enhancement is attributed to the higher sensitivity of the fuzzy optimization technique, which is calculated using real sensor data. The proposed model can also be effectively applied to monitoring delay behavior in IoT-based smart manufacturing networks. Furthermore, integrating neuro-fuzzy techniques into the model in future research could further enhance its accuracy and robustness.

**CONCLUSION**

This study proposed a new approach for modeling and evaluating time delays that occur during the transmission of sensor data in smart manufacturing systems using fuzzy logic. Unlike traditional deterministic models, the presented method effectively captures uncertainty, nonlinearity, and network variability in production processes. Based on these principles, a Takagi–Sugeno (T–S) type fuzzy time-delay model was developed. Using data from ten sensors, fuzzy membership functions were designed and their triangular boundaries were defined and adjusted.

By performing computations with the derived analytical formulas, the overall fuzzy delay was found to be seconds. Similarly, the **system efficiency,** evaluated through fuzzy analysis, was obtained which exceeds the minimum required threshold This confirms that the smart manufacturing system operates in a stable and optimal state under real-time control conditions.

The proposed approach can be effectively applied to smart manufacturing, IoT (Internet of Things), and cyber-physical systems for optimizing real-time monitoring and control mechanisms. The fuzzy model enables detailed analysis of signal delays, evaluation of system efficiency, and reduction of error rates. Moreover, for production lines requiring high precision, this method enhances manufacturing quality and helps reduce process failure risks.

This approach can be effectively used to optimize real-time control mechanisms in smart manufacturing, IoT (Internet of Things), and cyber-physical systems. Using a fuzzy model, it is possible to analyze signal delays, evaluate system efficiency, and reduce errors. Especially in production lines where high accuracy is required, this method increases production quality and reduces the risk of process failures.

Thus, the proposed fuzzy time-delay model serves as an important theoretical and practical basis for improving the stability and reliability of smart manufacturing systems.

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