Fuzzy Logic Based Adaptive Parameter Estimation System in Moving Measurement Systems

ZUHAL ER[1], BARIŞ GÖKÇE[2], SALIH METIN YURTER[3]
[1]Maritime Faculty, Istanbul Technical University (ITU), Istanbul, TÜRKIYE
[2]Deparmentt of Mechatronic Engineering. Faculty of Engineering, Necmettin Erbakan University, Konya, TÜRKIYE
[3]Zenopix Technology Industry and Trade Limited Company, Necmettin Erbakan University, Ankara, TÜRKIYE

Abstract: -Fast and accurate weighing of the weighing systems used in industrial filling systems is of great importance in terms of increasing production capacity and maintaining product quality. In facilities that grind and process grain, machines and equipment are positioned horizontally and vertically on steel structures. Since these machines continuously perform grinding, transferring, filling, and emptying operations, they create continuous vibration in the mechanical systems they are connected to. Moving weighing systems are significantly affected by these mechanical systems. When the impact effect of pneumatic valves-controlled covers in moving weighing systems is added to these structural mechanical vibrations, there are significant waits and delays in weighing systems that measure performance. For this reason, in a performance measurement system in a flour mill, the measurement interval increases as the amount of weighing increases. For example, in a moving weighing system that performs 50 kg performance weighing, the measurement interval can increase up to 15 seconds, which is quite long. In this study, an applied study has been conducted to increase the weighing performance in moving weighing systems and to minimize the measurement interval. The data collection process in the study focuses on two main components: load cell data and IMU data. Thus, it is aimed to overcome the difficulties of traditional methods used in weighing systems, which are generally observed to be insufficient to combat slow and noisy data. The analysis techniques used in this study are Kalman Filtering, Dynamic Q and R Matrix Updates, Comparative Analysis and Statistical Analysis. The Kalman filter was used for the integration of Load cell and IMU data and was applied to filter out noise and oscillations in the weighing data and make more accurate weight estimates. The results obtained showed that the dynamic Kalman filtering method can provide faster and more accurate weighing results compared to traditional methods, with error rates varying between 0.4% and 1% for different combinations of Q and R values in measurements made on the scale. Dynamic Kalman filtering method effectively filters oscillatory and noisy load cell signals, with error rates of 0.7% to 1% for Q=0.02 and R=17 parameters, and error rates of 0.4% to 0.7% for Q=0.07 and R=13 parameters. was able to obtain more accurate weight estimates. This study has shown that the dynamic Kalman filtering method is a potential method that can be used in industrial filling systems. This method can contribute to increasing production capacity and maintaining product quality by providing faster and more accurate weighing results. In this respect, the research has a unique contribution. This method provides a revolutionary development in industrial weighing systems and fills an important gap in the literature.

Key-Words: -Kalman filter, Fuzzy logic, Dynamic measurement, Inertial measurement unit, Load cell

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1. Introduction

Mobile measurement systems are systems used to collect accurate and reliable data in dynamic environmental conditions. These systems are widely used in various application areas, for example, robotics, vehicle control, aircraft, marine vessels and mobile sensor networks. Fuzzy logic-based adaptive parameters are used to increase the performance of such systems. In today's modern industrial systems, weighing is a critical process control phase. In raw material and related sectors, the need for fast and precise weighing is increasing day by day. The grain industry is also at the forefront of these sectors [1], [2]. Active weighing systems are systems used in the grain industry to weigh products such as wheat, flour and bran during production, without interrupting production. Thanks to the efficiency systems with advanced technological infrastructure, production-related information such as capacity and efficiency values can be easily accessed at any time while production continues. In this context, it is critical that the measured values exactly match the real values. Even the slightest error in measured values can lead to huge financial losses in mass production factories. The use of the dynamic weighing method in the grain industry and related production systems provides an increase in the amount of product weighed per unit time due to the products being in motion. In this way, time and economy are saved [1], [3], [4]. In the dynamic weighing method, in order to reach the desired weighing speeds, the products must be weighed without stopping; However, mechanical vibrations and environmental harmonics may cause distortions in the measurement signal that vary depending on the speed of the moving system and the weight of the object to be measured [5]-[7], [17], [18], [27]-[30].

Load Cells are generally used as weight sensors in weighing systems. The combination of load cells with an oscillatory response due to their nature and the low-frequency disturbance caused by vibrations in the system results in a noisy measurement signal [6], [19], [31]. It is very difficult to separate these disturbing effects, which occur from mechanical and structural effects, from the measurement signal. To correct the system response, filtering of the measurement signal is generally used [5]. Generally speaking, when we look at the literature, passive vibration reduction approaches are used in engineering applications when the general characteristics of vibration are known, but over time, both structural changes and modifications on the system may cause problems with low-frequency vibrations [8], [9], [20]-[32].

With the advancement of technology, new types of actuators and sensors are emerging, and with the cheaper computing technology, active vibration control has become applicable to many problems [10], [11], [32]. While different numerical models are designed to create active vibration control algorithms, it is important that the dynamic properties of the structure to be measured must be preserved throughout the control or measurement process. This enables the adjustment of some controllers used to reduce or characterize vibration, such as positive position feedback (PPF) [9], [11], while controls to be made with algorithms such as linear quadratic (LQ) [10], [12] or model estimation. [13], [14] enable results to be obtained in different ways.

In industrial filling systems, especially in grain processing facilities, high-precision and high-speed weighing operations are critical for production efficiency and product quality. The continuous movement of machines and equipment in these facilities causes significant vibrations in the associated structural systems. These vibrations negatively affect the measurement accuracy of moving weighing systems, leading to delays and erroneous results in weighing processes. The impact effect of pneumatic valves, in particular, further exacerbates these negative effects. This study aims to investigate ways to improve weighing performance and reduce measurement times in moving weighing systems in grain processing facilities. To this end, dynamic parameters were determined using the Kalman filtering method with load cell and Inertial Measurement Unit (IMU) data. The primary objective of the study is to develop a model to obtain more accurate and faster weighing results, despite the adverse effects of vibrations and external factors

2. Materıals and Methods

In this study, MPU6050 was used as the IMU and STM32F407V series 168 MHz processor was used as the microcontroller. Figure 1 shows the microcontroller used in the study. Through this control card, the UART communication output was connected to the computer with a UART-USB converter and the module was made ready for data transfer.

Fig. 1. Data collection card used

The data collection module connection is seen in figure 2. The Control Card is placed in two different orientation positions on the mobile grain weighing system. The reason for using two different sensor modules was that the sensitivity of the acceleration movement in the Z axis would be low, and the two cards were placed at a 90-degree angle to each other. Thus, more accurate data was obtained. Both cards were placed in the chamber within the measurement system, thus creating a data collection environment that could absorb all the noise that the weighing system would be exposed to.

Fig. 2. Control system connected to active weighing system

3. Results and Dıscussıons

Figure 3 shows the acceleration values on the X axis from the data taken in the measurement environment. From the amplitude value given here, it can be seen that periodic accelerations or noise occur.

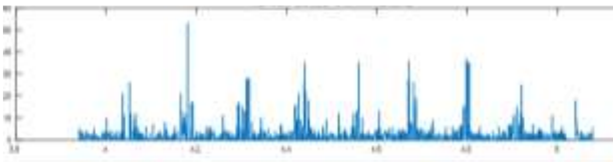

Fig. 3. X-axis acceleration value of the mobile weighing system

Figure 4 shows the acceleration amplitudes of the Y axis to which the control system is connected. When these values are compared with the X-axis acceleration values in the previous graph, it is seen that the oscillation is not much in the Y direction. This direction is actually 90 degrees perpendicular to the pneumatic valves. In this way, limitation in one direction affects the vibration.

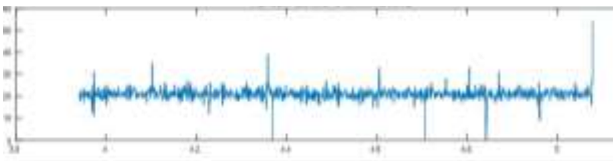

Fig. 4. Y-axis acceleration value of the mobile weighing system

Figure 5 shows the Z axis acceleration value of the mobile weighing system. Here, it has been observed that in normal cases, no vibration is observed or the noise in the Z direction is very low due to the gravitational effect on the Z axis, but it has been observed that it has serious effects on the Z axis due to the knocking during opening and closing of the covers connected to the pneumatic pistons. This situation affects the weighing process extremely negatively.

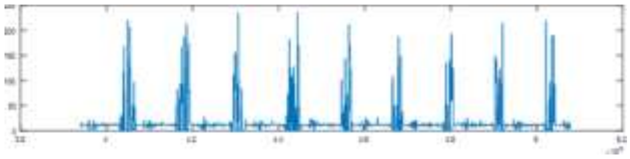

Fig. 5. Z axis acceleration value of the mobile weighing system

These noises in the Z axis are the noises created by the system's moving elements (pneumatic systems, etc.) and the released elements in the system (joints, etc.). These noises completely change the measurement characteristics. Therefore, it was concluded that it would be more accurate to determine the parameters by taking into account the effects of these elements in order for the selected filters to be adaptive.

Noise was eliminated by applying a Kalman filter on the Z-axis speed and position displacement values in the active weighing system. After removing the noise, RMS values were obtained for speed and position change. Accordingly, the RMS values of speed and position change are RMSpeed = 0.51; RMSposition = 0.46.

Figure 6 shows the Z axis speed change value over rms value graph in the active weighing system. When this graph is compared with the previous graph, the noise effect of moving and free elements on the measurement between measurement periods is clearly seen. If you pay attention, the noise characteristics in each period are not the same. Therefore, if the noises within a 120-second measurement are taken as reference, the filter parameters can be determined as accurately as possible. As can be seen here, position changes occur in both directions of the axis and position changes are very high due to moving free elements during measurement. Here too, taking displacement values above the RMS values enabled the grouping of the data's measurement periods.

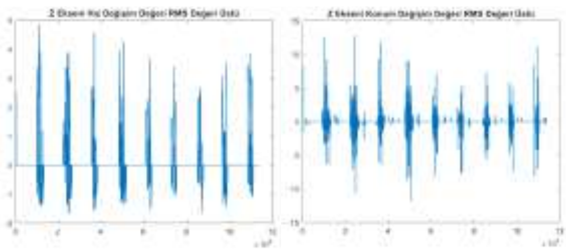

Fig. 6. Z axis Speed and Position Change Value in the active weighing system is above the RMS Value

Within the scope of this study, adaptive adjustment of the fuzzy logic-based measurement noise covariance matrix R or process noise covariance matrix Q was provided. Adaptively specifying these parameters improves Kalman filter performance and prevents the filter from biasing when R or Q are uncertain.

In dynamic weighing systems, mechanical covers create delays in weighings due to physical constraints during stops and starts. These physical constraints and time delays impose certain acceptable time intervals for measurements. For example, in grain performance weighing systems, weighing intervals vary between 5 and 15 seconds. Generally, the first 4-5 seconds of this interval is due to mechanical constraints.

This fuzzy logic based adaptive Kalman filter was tested on a digitally developed weighing system. It has been observed that the fuzzy logic based adaptive Kalman filter gives much better performance at acceptable phase shift.

An algorithm using fuzzy logic principles has been created to adaptively adjust the Q and R matrix of the noise covariance matrix. Speed and position data derived from acceleration data received from the IMU sensor were used in the fuzzy logic design. Speed and position data here play a key role in determining noise during measurement. The obtained average speed and position data were used as fuzzy logic input set membership function data. At this stage, minimum and maximum speeds and position displacements are given in Table 1.

Table 1. Inimum and Maximum Values of Speed and Position Data

	Minimum	Maxsimum	Average
Speed	0	5	3,71
Position	0	13	8,88

At this stage, a fuzzy logic inference system with two inputs and two outputs is designed. This system was made for both Mamdani and Sugeno. Speed and position data were determined as inputs, and Q and R values were determined for the outputs. For Mamadani, the "AND" method and minimum value were determined for two entries, and the center of gravity method was selected in the rinsing process. Figure 7. A visual representation of the Mamdani type fuzzy logic inference system is given. The selected features are also shown on the image.

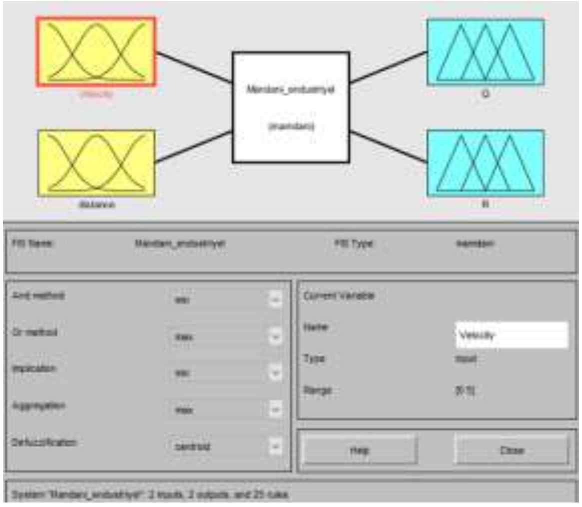

Fig. 7. Visual demonstration of mamdani type fuzzy logic inference system

Speed and location data were used as input. In Table 2, the velocity input membership function data is given, and in Figure 8, the graphical representation of the velocity input membership function data is given. Here, the input data is divided into five fuzzy sets and determined as smallest (vs), small (s), medium (m), high (h) and highest (vh). Triangular membership function was preferred. While determining the minimum and maximum values of the data, 0 and the maximum value were determined by rounding the highest speed value read on the weighing system to the upper integer.

Table 2. Velocity Input Membership Function Data

Velocity Input Membership Function			
Vs	0	0,75	1,50
S	0,25	1,5	2,5
M	1,5	2,5	3,5
H	2,5	3,5	4,75
Vh	3,5	4,25	5

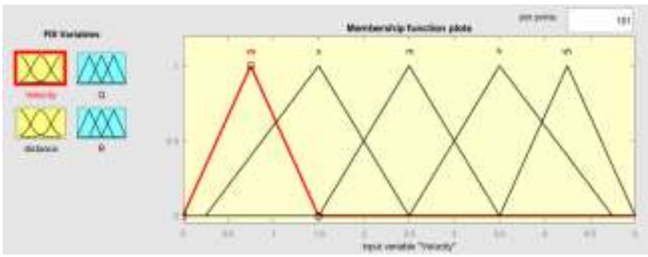

Fig. 8. Graphical representation of velocity entry membership function data

Figure 9 shows the graphical representation of the distance input membership function. As in the velocity table, a triangular membership function was used here and the data was determined by rounding the data from 0 to the maximum displacement data to the upper integer. Here, the creation of a triangular membership function has been determined entirely based on experience.

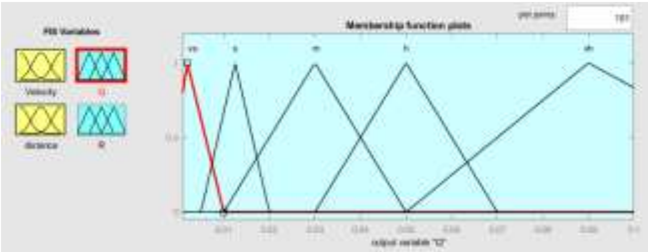

Fig. 9. Graphical representation of Q Parameter output membership function

Figure 10 shows the graphical representation of the Q parameter output membership function. Determining the output of this parameter is based entirely on observation. The lowest Q value completely eliminates noise by making a very flat prediction at the filter output and creates a noticeable phase shift. The lowest acceptable Q value observed on the scale is 0.001. This value is the minimum value that can be used if there is very high speed and very large positional displacement. If it is for the lowest speed and smallest positional displacement, the highest Q value that can be used is 0.1. Fuzzy inference will make an inference in the meantime.

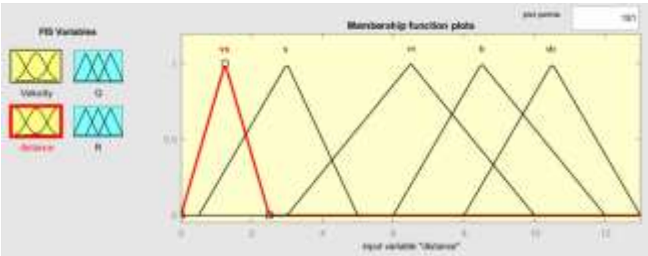

Fig. 10. Graphical representation of distance entry membership function

Figure 11 shows the graphical representation of the R parameter output membership function. As can be seen from here, the change in R affects the output with a linear change, not with an exponential change like Q.

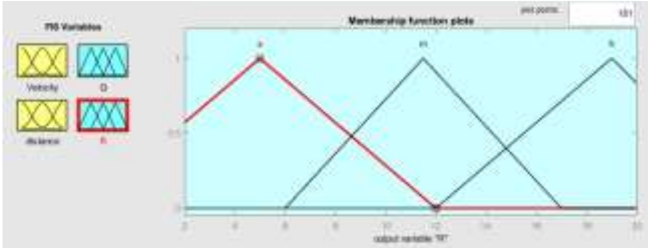

Fig. 11. R parameter output membership function graphical representation

Table 3 gives the rule table defined for output. While creating the rule table defined for the output, the output definition according to the inputs was determined according to the effect of 40% speed and 60% position change. Since this proportional determination has a greater effect of spatial displacement on noise than speed, output memberships were determined according to this rule.

Table 3. Rules Definations

	Velocity	Distance	Q	R
1	VS	VS	VH	S
2	VS	S	H	S
3	VS	M	H	M
4	VS	H	M	M
5	VS	VH	M	H
6	S	VS	VH	S
7	S	S	H	S
8	S	M	M	M
9	S	H	M	M
10	S	VH	S	H
11	M	VS	H	S
12	M	S	H	M
13	M	M	M	M
14	M	H	S	H
15	M	VH	S	H
16	H	VS	H	M
17	H	S	M	M
18	H	M	M	H
19	H	H	S	H
20	H	VH	VS	H
21	VH	VS	M	M
22	VH	S	M	M
23	VH	M	S	H
24	VH	H	S	H
25	VH	VH	VS	H

The distribution of these inferences made for Mandani on the membership functions is given in figures 12, 13, 14 and 15.

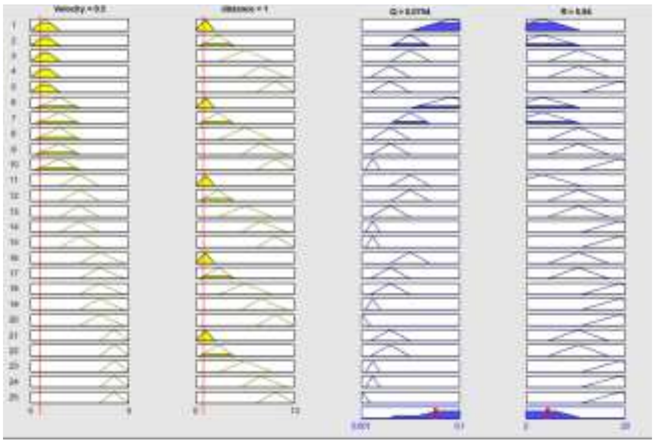

Fig. 12. Mamdani Fuzzy Logic Inference Example Input Speed = 0.5, Position = 1 for Q = 0.07 , R = 6

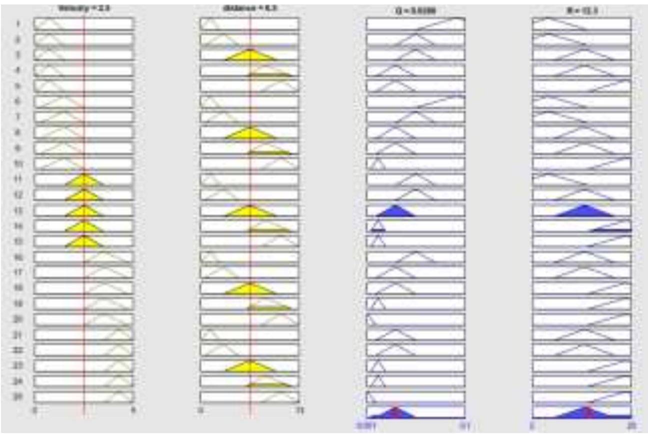

Fig. 13. Mamdani Fuzzy Logic Inference Example Input Speed = 2.5, Position = 6.5 for Q = 0.028 , R = 12

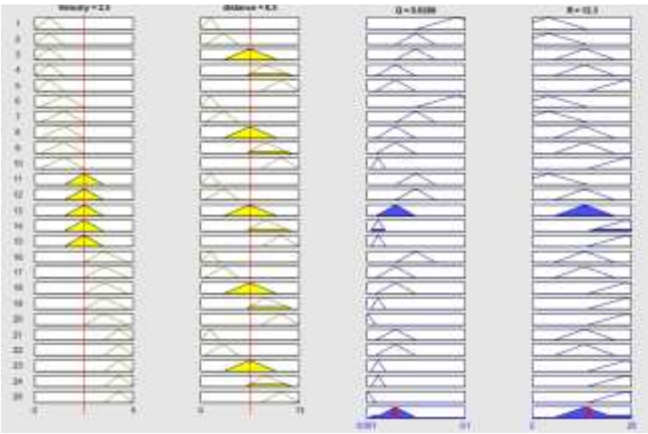

Fig. 14. Mamdani Fuzzy Logic Inference Example Input Speed = 4,9, Position = 12.9 for Q = 0.005, R = 16

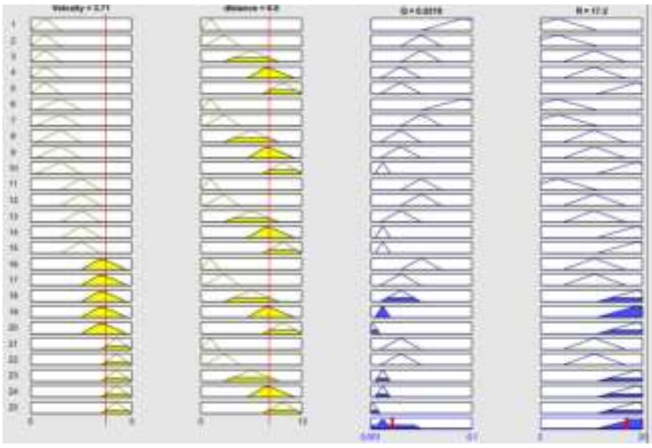

Fig. 15. Mamdani Fuzzy Logic Inference Example for Input Speed = 3.71 and Position = 8.8 , Q = 0.02 and R = 12

The same fuzzy logic inference was also made in the Sugeno method, which gives linear output. The distribution of these inferences made for Sugeno on the membership functions is given in figures 16, 17, 18, and 19.

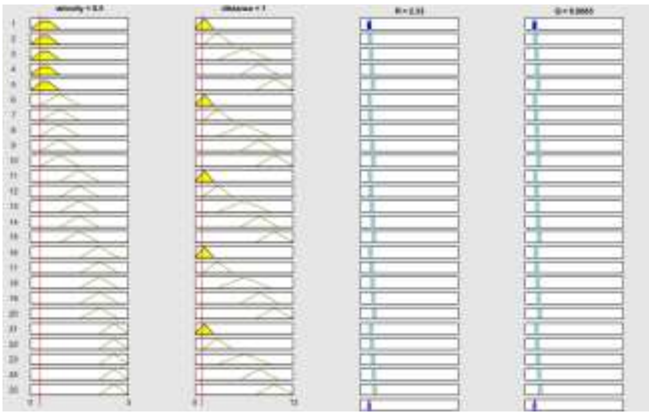

Fig. 16. Sugeno Fuzzy Logic Inference Example for Input Speed=0.5 and Position=1, Q=0.1 R=2

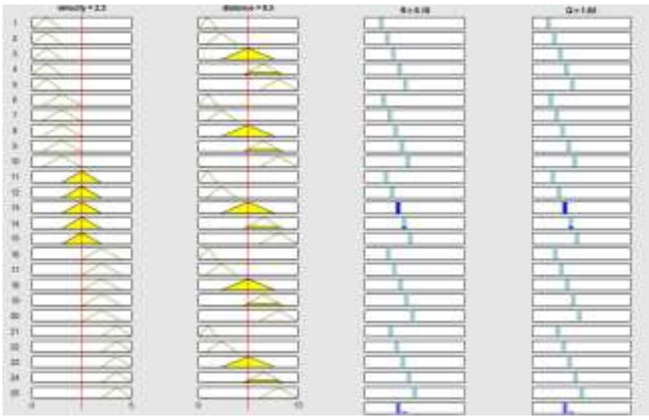

Fig. 17. Sugeno Fuzzy Logic Inference Example for Input Speed=2.5 and Position=6.5, Q=0.09 R=8

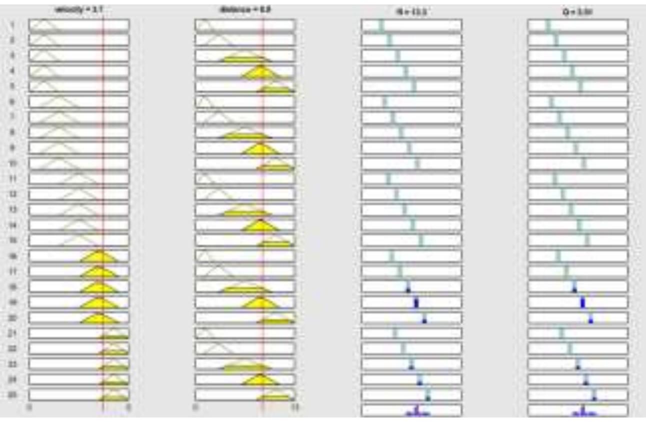

Fig. 18. Sugeno Fuzzy Logic Inference Example for Input Speed=3.7 and Position=8.8, Q=0.07 R=13

Fig. 19. ugeno Fuzzy Logic Inference Example for Input Speed=4.9 and Position=12.9, Q=0.001 R=17

Figure 20 shows the Sugeno fuzzy logic software interface made in Python.

```
@author: baris gokce
SUGENO FUZZY INFERENCE SYSTEM
"""
import numpy as np
import array as arr

def triangle(input_data, Sensor_data):
    aa = Sensor_data[0];
    bb = Sensor_data[1];
    cc = Sensor_data[2];
    if input_data <=aa or input_data >= cc:
        Value=0;
    elif input_data > aa and input_data < bb:
        Value=(input_data-aa)/(bb-aa);
    elif input_data == bb:
        Value = 1;
    elif input_data > bb and input_data < cc:
        Value = (cc-input_data)/(cc-bb);
    else:
        Value = 0;
    return Value;

velocity_in = 2.5;
distance_in = 6.5;
## a,b,c Q parametresi icin cikis katsayilari icin ustel bir fonksiyon olusturuldu
## f(x) = a*x^b+c
a_Q=0.001094;
b_Q=2.776;
c_Q=0.003241;
```

Fig. 20. Mamdani Fuzzy Logic Software Made in Python Programming Language

When the Table 4 is examined for the fuzzy inference results obtained with Mamdani and Sugeno, it is seen that the linear inference results obtained from Sugeno are more meaningful and closer to reality.

Table 4. Table Type Styles

	Velocity	Position	Q	R
Input	Sugeno			
1	0,5	1	0,1	2
2	2,5	6,5	0,09	8
3	4,9	12,9	0,001	21
4	3,71	8,8	0,07	13
Input	Mamdani			
1	0,5	1	0,07	6
2	2,5	6,5	0,028	12
3	4,9	12,9	0,005	16
4	3,71	8,8	0,02	17

Figure 21 shows Mamdani fuzzy inference results and original weighing data graph, final weighing result graph using Kalman filter with parameter defined for Q=0.02 and R=17. Here, it has been observed that for the coefficients R = 17, Q = 0.02, the error rate is 0.7% in 6 weighings, 0.9% in 7 weighings and 1% in 8 weighings. The reason for the increase in the error rate can be attributed to the increased phase lag between the raw data and the filtered data as the system better suppresses noise. As the phase shift increases, the error also increases significantly, resulting in a longer weighing time. The data obtained as a result of weighing were as shown in Figures 22 and 23, respectively.

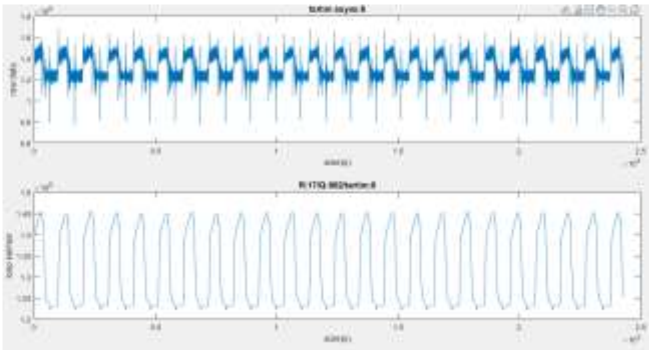

Fig. 21. R:17 Q:002 Number of Weighings:6

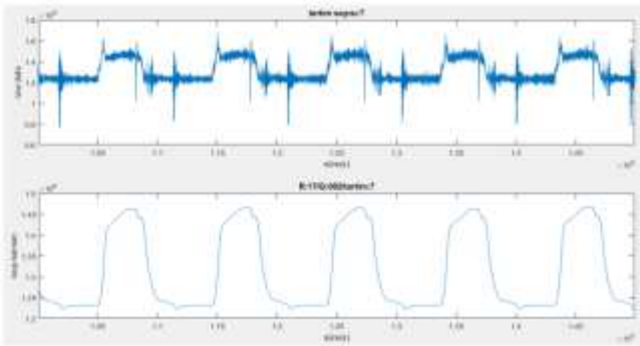

Fig. 22. R:17 Q:002 Number of Weighings:7

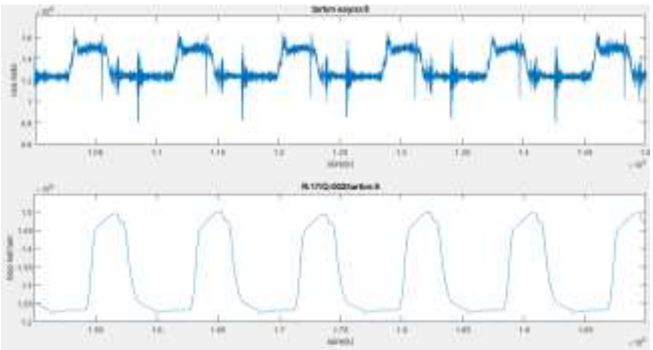

Fig. 23. R:17 Q:002 Number of Weighings:8

Figure 24 shows the original weighing data and graph of Sugeno fuzzy inference results, data graph results using Kalman filter with parameter defined for Q=0.07 and R=13. It has been observed that the system works successfully with an error rate of 0.4% in 6 weighings, 0.6% in 7 weighings and 0.7% in 8 weighings for the coefficients R = 13, Q = 0.07. The data obtained as a result of weighing were as shown in Figures 25 and 26, respectively.

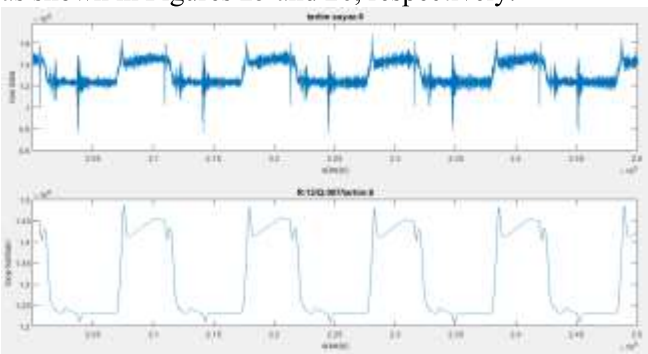

Fig. 24. R:13 Q:007 Number of Weighing:6

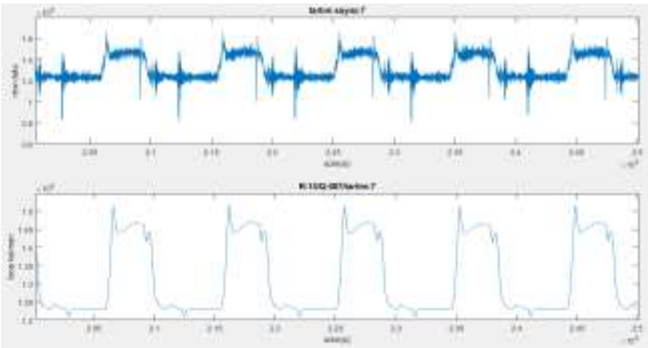

Fig. 25. R:13 Q:007 Number of Weighing:7

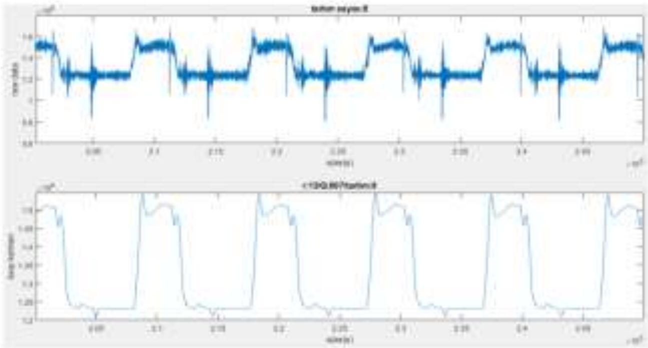

Fig. 26. R:13 Q:007 Number of Weighing:8

The available studies focusing on dynamic parameter estimation with the Kalman filter method using acceleration, velocity and position data are presented in the Table 5.

Table 5. Comparison of This Study with the Literature

Refrences	Main Theme	Application Area
[1], [2], [5], [6], [7], [17], [18], [20], [27], [28], [29], [30],	Dynamic Weighing	Continuous mass measurement in checkweighers, dynamic compensation, dynamic load identification
[1], [21], [22], [23], [24], [25], [26]	Kalman Filter	attitude estimation, state estimation, adaptive filtering
[8], [9], [10], [11], [12], [13], [14], [15], [16],	Mechanical Vibration	LQG control of vibrations in flexible structures, vibration control of active structures.
This study	Kalman filter, mobile measurement, load cell, IMU sensor,	As can be seen above, this study shares common aspects with other studies in the literature, but it offers originality in its practical application. By eliminating environmental and structural vibrations

	mobile grain, weighing system, Estimation, Measurement, fuzzy logic inference system, membership function, acceleration, velocity, position	that occur during dynamic grain weighing, it accelerates the weighing process. This is achieved by estimating dynamic parameters using the Kalman filter method with raw load cell data and acceleration, speed, and position data obtained from the IMU sensor. This approach allows for faster weighing.

4. Conclusıons

Active farming systems produce very noisy measurement results due to both the mechanical and structural vibrations of their environment and various external factors. This can lead to deviations in measurement values and sometimes even serious measurement errors. While measurements are made relatively quickly in non-dynamic structural systems, filtering measurements of vibrations on dynamic and moving systems and vibrations on a dynamically operating system is very important for the industrial sector.

In this study, filters that can be used for measurements of moving weighing systems and the effects of these filters on measurement and performance characteristics were investigated. The results obtained allowed the development of a fuzzy logic-based parameter extraction system to update the coefficients of the active filters used.

In this study, Mamdani and Sugeno fuzzy inference methods were combined with the Kalman filtering technique to reduce measurement errors in moving weighing systems. While both methods yielded successful results to a certain extent, the Sugeno method was observed to improve system performance with lower error rates.

Mamdani Method: In the Mamdani method, although the obtained results suppressed the noise in the system better, they caused an increase in the error rate due to the phase shift between the raw data and the filtered data. This situation is undesirable, especially in applications requiring high precision.

Sugeno Method: The Sugeno method, on the other hand, was successful in both noise suppression and minimizing phase shift, resulting in lower error rates. This result indicates that the Sugeno method is more suitable for such applications.

In conclusion, a fuzzy logic-based parameter update system has been developed to increase the measurement accuracy in moving weighing systems. In this system, it has been observed that the Sugeno method is more successful and provides significant improvement when used with Kalman filtering. The obtained results indicate that this method can also be used in different industrial applications

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Declaration of Generative AI and AI-Enabled Technologies in the Writing Process

During the preparation of this study, only the authors used ChatGPT4.0 mini for grammar and language checking. After using this tool/service, the authors reviewed and edited the content as necessary and assumes full responsibility for the content of the publication.

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