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Research Article

Tekstil Endüstrisi İçin Yeşil Dönüşüm Odaklı Enerji Modeli: Bir Ramöz İçin Isı Geri Kazanımı

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Anahtar Kelimeler
Isı Geri Kazanımı,
Bulanık Mantık,
Enerji Verimliliği,
Yakıt Tüketimi,
Hava Akış Hızı,
Yeşil Dönüşüm

Öz: Germe makineleri, kumaşları kurutmak için sıcak hava kullanarak tekstil endüstrisinde hayati bir rol oynamaktadır. Bu sıcak havanın önemli bir kısmı atık olarak dışarı atılmakta ve önemli enerji kaybına neden olmaktadır. Bu çalışma, bulanık mantık tabanlı bir performans modeliyle desteklenen, germe makinesine entegre edilmiş bir ısı geri kazanım (HR) sisteminin etkisini araştırmaktadır. Gerçek zamanlı proses verileri, HR sistemi uygulanmadan önce ve sonra bir tekstil tesisinden toplanmıştır. Bu ölçümler kullanılarak, değişen hava akışı ve geri dönüş hava oranları altında yakıt tüketimini ve çıkış nem içeriğini tahmin etmek için Mamdani tipi bir bulanık çıkarım modeli geliştirilmiştir. Model, %1,86'lık ortalama mutlak hata ile yüksek tahmin doğruluğu göstermiştir. HR uygulamasından sonra %18'e varan yakıt tasarrufu sağlanmıştır. Literatürde ilk kez, bu araştırma, tekstil ısı geri kazanımı uygulamasında deneysel ölçümleri bulanık mantık modellemesiyle birleştirmektedir. Sonuçlar, bulanık mantık sistemlerinin endüstriyel enerji optimizasyon süreçlerinde belirsizliği ve doğrusal olmayanlığı etkili bir şekilde yönetebileceğini vurgulamaktadır. Bu çalışma, tekstil kurutma sistemlerinde enerji verimliliğini artırmak ve çevresel etkileri azaltmak için doğrulanmış bir karar destek yaklaşımı sunmaktadır.

Green Transformation-Oriented Energy Model for the Textile Industry: Heat Recovery for a Stenter

Keywords
Heat Recovery,
Fuzzy Logic,
Energy Efficiency,
Fuel Consumption,
Air Flow Rate,
Green Transformation

Abstract: Stenter machines play a vital role in the textile industry by using hot air to dry fabrics. A substantial amount of this hot air is exhausted as waste, resulting in significant energy loss. This study investigates the impact of a heat recovery (HR) system integrated into a stenter machine, supported by a fuzzy logic-based performance model. Real-time process data were collected from a textile plant both before and after the HR system was implemented. Using these measurements, a Mamdani-type fuzzy inference model was developed to predict fuel consumption and outlet moisture content under varying airflow and return air ratios. The model demonstrated high prediction accuracy with a mean absolute error of 1.86%. After HR implementation, up to 18% fuel savings were achieved. This research combines experimental measurements with fuzzy logic modeling in a textile heat recovery application. The results highlight that fuzzy logic systems can effectively manage uncertainty and nonlinearity in industrial energy optimization processes. This study provides a validated decision-support approach for improving energy efficiency and reducing environmental impacts in textile drying systems.

1. Introduction

This study follows a systematic methodology consisting of real-time data collection from a stenter machine, heat recovery implementation, fuzzy logic modeling, and experimental validation. The process is designed to evaluate how heat recovery affects fuel consumption and outlet moisture under varying operating conditions. A Mamdani-type fuzzy inference system was developed using airflow rate and return air ratio as inputs and fuel consumption and outlet moisture as outputs. The model was constructed in MATLAB and validated using experimental measurements taken from an operational stenter line in an industrial textile facility. A Mamdani-type fuzzy inference system was selected due to its suitability for systems with uncertainty and nonlinearity. Two input variables were used: airflow rate and return air ratio. Two output variables were defined: fuel consumption and outlet moisture. Each variable was divided into fuzzy sets using Generalized Bell Membership Functions (GBellMF). A total of 300 fuzzy IF-THEN rules were constructed based on expert knowledge and system behavior. The centroid defuzzification method was applied to obtain crisp outputs. The fuzzy inference system was implemented using MATLAB's Fuzzy Logic Toolbox. Stenter machines are extensively used in textile finishing processes, where hot air is utilized to dry textile materials by transferring thermal energy and removing residual moisture. During operation, a significant portion of the hot air is exhausted as waste, carrying both heat and moisture, which leads to considerable energy losses if not recovered efficiently. Ramous exhaust air contains a certain amount of moisture. If the amount of moisture in the exhaust air is low, it indicates that the moisture holding capacity of the air cannot be utilized sufficiently. If the amount of moisture is high, mass transfer slows down and there is a possibility of condensation. Heat Recovery (IGK) refers to the recovery of the energy carried by the waste gases and its use in the preheating of the process air. With this application, energy savings are achieved without reducing the process air temperature.

Studies in the literature: In a 2019 study, Ciappi and her team evaluated the efficiency of air curtains used in the textile industry. They conducted tests on different air curtain angles, factory speeds, air flow rates, and temperatures. The research showed that selecting the correct air curtain temperature and flow rate provided the best efficiency, while the inclination of the air curtain had a limited effect on performance. It was found that air curtains improved machine performance, reduced heat loss, and provided energy savings. The study suggested using hot air curtains at low speeds and cold air curtains at high speeds, highlighting the potential of air curtains to increase energy efficiency in the textile industry (Ciappi et al., 2019). The study by Karacavus and Hamzaoğlu examined the impact of using economizers on energy efficiency in stenter machines. It was noted that economizers reduce energy consumption by using the heat from waste air to warm the cold air. The study demonstrated that the use of economizers resulted in a 20.95% savings in energy costs. It was emphasized that economizers have the potential to reduce natural gas and electricity consumption and improve energy efficiency in the textile industry (Karacavus & Hamzaoğlu, 2012). In a 2015 report, Hasanbeigi and Price evaluated innovative technologies that provide energy and water efficiency as well as pollution reduction in the textile industry. The report detailed various technologies such as Nanoval technology and supercritical CO_2 dyeing, discussing their energy and environmental benefits as well as their commercialization status. The report offered recommendations and strategies to enhance sustainability in the textile industry (Hasanbeigi & Price, 2015). In 2013, Aghbashlo and his team examined the enthalpy analysis of drying processes. The paper evaluated the energy and enthalpy efficiency of various drying methods and demonstrated how enthalpy analysis could be used to optimize drying systems. It emphasized that enthalpy analysis is crucial for increasing energy efficiency and reducing environmental impacts (Aghbashlo et al., 2013). In 2007, Cay and colleagues used artificial neural networks (ANN) to predict the air permeability of woven fabrics. The research showed that ANNs are an effective tool for solving complex problems in the textile and apparel technology field and that modeling air permeability and water content can aid in optimizing the industrial drying process (Cay et al., 2007). Jariwala and his team developed a Fuzzy Rule-Based System (FRBS) in 2020 to predict worker health risks in textile processing operations. The study revealed that the working environment in dyeing and printing facilities falls into a high-risk category and that workers face significant health risks. The study demonstrated that FRBS can be used to predict worker health risks and improve working conditions (Jariwala et al., 2020). In 2012, Şekkeli and Keçecioğlu conducted a study showing that a waste heat recovery system (WHRS) in textile factories could save energy. They controlled the WHRS using a SCADA system and noted significant thermal energy savings. Despite the additional electrical consumption required for WHRS installation, the heat gain and cost savings it provided offset these costs. The study highlighted the importance of improving energy efficiency and reducing environmental issues (Şekkeli & Keçecioğlu, 2012). In 2014, Fayala and his team proposed a fuzzy logic-based method to identify the parameters affecting the thermal conductivity of stretched knit fabrics. The research showed that parameters such as knit structure, Lycra content, yarn count, and thickness have decisive effects on thermal conductivity. The study demonstrated that artificial intelligence systems could be used to understand and optimize thermal comfort parameters in the textile industry (Fayala et al., 2014). In recent years, fuzzy logic modeling methods have been used effectively in drying processes not only in the textile but also in the food, paper and ceramics industries . These studies show that fuzzy logic is a powerful estimation tool in uncertain systems. While prior studies explored heat recovery or fuzzy modeling separately, this research uniquely integrates both approaches and validates the fuzzy model experimentally under real factory conditions. This contribution fills a notable gap in the intersection of process optimization and AI-assisted control in textile finishing.

Instead of discharging hot air from the chimney, cold air taken from the factory environment is heated and fed into the machine. To prevent energy loss in this way, a portion of the humid air exiting the dryer, which contains heat energy, is mixed with clean air, heated, and reused. The ratio of this amount to the total drying air is called the return air ratio. The proportion of air passing through the dryer that is discharged to the outside versus the amount reused can be adjusted by opening and closing the dampers at the exhaust outlets. Unlike laboratory-based studies, this work evaluates heat recovery performance directly under industrial production constraints using manufacturer-defined operating limits and verified plant observations. The study therefore provides an application-oriented assessment and a decision-support modelling framework for real manufacturing environments.

In this study, the relationships between airflow, outlet moisture, and fuel consumption in a stenter machine were examined using fuzzy logic modeling. This approach aimed to determine optimal conditions for waste air management and energy savings. The data used were obtained from a stenter machine in a textile factory. The data were collected by moisture sensors, airflow measurement devices, and fuel consumption meters. Measurements were taken both before and after the implementation of the heat recovery system (HRS). The fuzzy logic model was used to process uncertain and imprecise data. In constructing the model, airflow and moisture content were used as input variables, while fuel consumption and outlet moisture were used as output variables. Fuzzy rules were established to define the relationships between these variables. This study modeled the optimization of moisture and fuel consumption after heat recovery in stenter machines with fuzzy logic (Mamdani model), providing such a level of accuracy (1.86% margin of error) for the first time for industrial textile processes. Both modeling and experimental comparison were made in this context. In this context, the present study aims to develop and validate a fuzzy logic-based control model to optimize fuel consumption and outlet moisture parameters in a stenter machine after the implementation of a heat recovery system (HRS). The proposed model is experimentally supported and offers a novel approach to managing uncertainty and nonlinearity in industrial drying processes. Although the previous studies explored the applications of heat recovery or intelligent modeling methods, there is a lack of research work based on real-time industrial data directly measured from the operational stenter machines. Most of the previous research works are based on laboratory-scale assumptions or simulation results. This research work aims to validate the industrial-scale heat recovery system using the real-time industrial data, and a decision model based on fuzzy logic is proposed for energy optimization.

The developed model was tested with experimental data collected from the stenter machine under various operating conditions. Comparisons between predicted and observed values revealed a strong correlation, demonstrating that the fuzzy logic model could serve as a reliable decision support tool for industrial drying optimization.

2. Materials and Methods

Heat recovery (HR) is the process of reusing waste heat. To enhance energy efficiency and achieve energy savings, waste heat generated in industrial processes or HVAC (Heating, Ventilation, and Air Conditioning) systems is recovered and reintegrated into the system. HR is a critical technique for reducing energy consumption, lowering costs, and minimizing environmental impacts. This method is widely used in energy-intensive industries, buildings, and transportation systems.

Energy efficiency, in this context, is evaluated by measuring the reduction in fuel consumption and improvement in moisture removal performance before and after the heat recovery application.

Fuel consumption denotes the amount of fuel used by a system over a specific period. Optimizing fuel consumption is vital for energy efficiency. HR applications help reduce fuel consumption by reusing waste heat, thereby lowering energy costs. Fuzzy logic models can analyze fuel consumption data to develop more efficient fuel usage strategies.

Airflow rate measures the volume of air passing through a system within a certain time frame. It is a critical parameter for energy efficiency and performance in HVAC systems and industrial processes. In HR systems, managing airflow rate correctly is essential for recovering and reusing waste heat. Fuzzy logic can analyze airflow rate data to determine optimal operating conditions for the system.

Moisture recovery rate indicates the proportion of moisture recovered within a system over a specific period. Effective moisture management is important, particularly in HVAC systems and industrial processes. HR applications can optimize the moisture recovery rate to enhance energy efficiency. Fuzzy logic models can analyze moisture recovery rate data to improve system performance and achieve energy savings.

"HR" stands for Heat Recovery, a process aimed at increasing energy efficiency and achieving energy savings by reusing waste heat. The term "Comparison

Before and After Heat Recovery" refers to evaluating the performance of a system before and after implementing heat recovery. Such comparisons assess reductions in energy consumption, increases in efficiency, and overall performance improvements. Measurements taken before and after HR implementation have shown that the fuzzy logic model yields successful results in both scenarios. In the post-HR period, significant improvements in waste air management and energy savings have been recorded.

The fuzzy inference system consists of two inputs (airflow rate and return air ratio) and two outputs (fuel consumption and outlet humidity). Each variable was described using Generalized Bell membership functions with three linguistic levels (Low–Medium–High). A total of 300 IF–THEN rules were defined based on operational behaviour of the stenter system and engineering knowledge of the drying process. Defuzzification was performed using the centroid method.

Stenter machines are extensively employed in the textile industry for drying textile products using hot air. Hot air enters the machine, transfers a certain amount of heat energy to the textile product, and exits carrying a certain amount of water vapor. The moisture content in the exhaust air indicates the efficiency of the drying process. Low moisture content suggests that the air's moisture-holding capacity is not being fully utilized, while high moisture content indicates slowed mass transfer and increased risk of condensation. Figure 1 shows a Stenter machine.

Figure 1. Stenter machine (DİLMENLER)

Figure 1 depicts a Stenter machine used for drying fabrics in the textile industry. Some details visible in the image are: Machine Structure: The Stenter machine comprises a large drying chamber, fabric transport systems, and control panels.

Brand: The machine shown is branded "DİLMENLER," a well-known name in textile machinery. Control Panels: The front part of the machine features digital screens and buttons used for monitoring and controlling the operation. Fabric Transport System: Rollers and belts ensure the smooth advancement of the fabric entering the machine. Air Channels and Pipes: Hot air is delivered to the machine through air channels and pipes, which is used in the drying process of the fabric. Exhaust Air System: After the drying process, the moist air exits the machine and is directed to the exhaust air system. This machine plays a crucial role in textile production processes. The hot air drying process ensures that fabrics reach the desired moisture level, which is essential for both energy efficiency and product quality. The working ranges employed in the model were established based on the technical specifications of the manufacturer's catalogue data and the actual working ranges of the stenter machine in the plant. The technical specifications of the manufacturer's catalogue data set the limits of operation of the machine in terms of its thermodynamic and flow characteristics. The actual process readings taken during normal operating conditions were employed to establish that the process was indeed working within the established limits. Consequently, the fuzzy logic model was developed to reflect the actual working conditions of the machine, as opposed to actual laboratory experiments. The airflow capacity, burner load, and possible return air ratios were established from the equipment manufacturer's documentation, while the fuel consumption and humidity characteristics were assessed based on the actual working conditions.

Fuzzy logic is a mathematical logic system that goes beyond traditional binary logic. Unlike binary logic, which deals with precise values, fuzzy logic works with data that contains uncertainty and imprecision. This approach results in outcomes that are closer to human reasoning. Fuzzy logic is particularly used in engineering, control systems, and artificial intelligence applications. In this study, a fuzzy logic model has been utilized to evaluate the performance of heat recovery (HR) systems. This allows for more flexible and realistic data analysis. Using MATLAB, a fuzzy logic model was developed to assess the performance of HR systems, and the results were examined. The Mamdani type fuzzy extraction system is widely used in industrial systems. System behavior can be easily described by linguistic conventions: For example, "If the humidity is high and the air flow rate is low, fuel consumption is high." The Mamdani model is suitable for drying and humidity control systems where there are a lot of uncertainties because it provides both accuracy and interpretability. A Mamdani model with two inputs and two outputs was constructed using the fuzzy logic module in MATLAB. In this model, the results were obtained using the centroid method. The centroid method produces a more balanced result by averaging all possible outputs. In cases where the output is distributed non-linear, the chances of reaching the optimum solution are higher. In the MATLAB fuzzy toolbox, the centroid method is widely supported and provides high resolution. The fuzzy logic model used in the problem-solving process is shown in Figure 2.

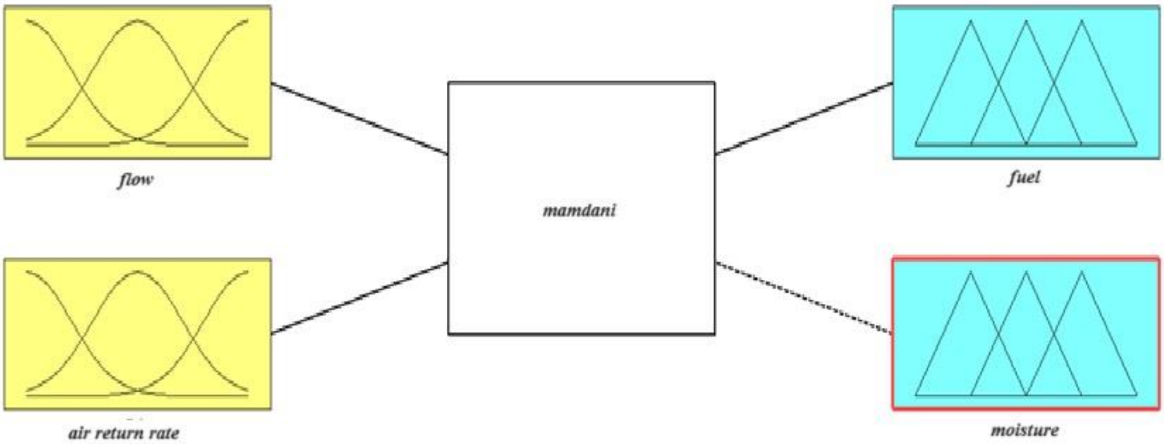

Figure 2. HR fuzzy logic model

The input is the flow to the first of the sets of membership functions. As shown in Figure 3, the values and ranges are processed into the fuzzy logic module of the MATLAB program.

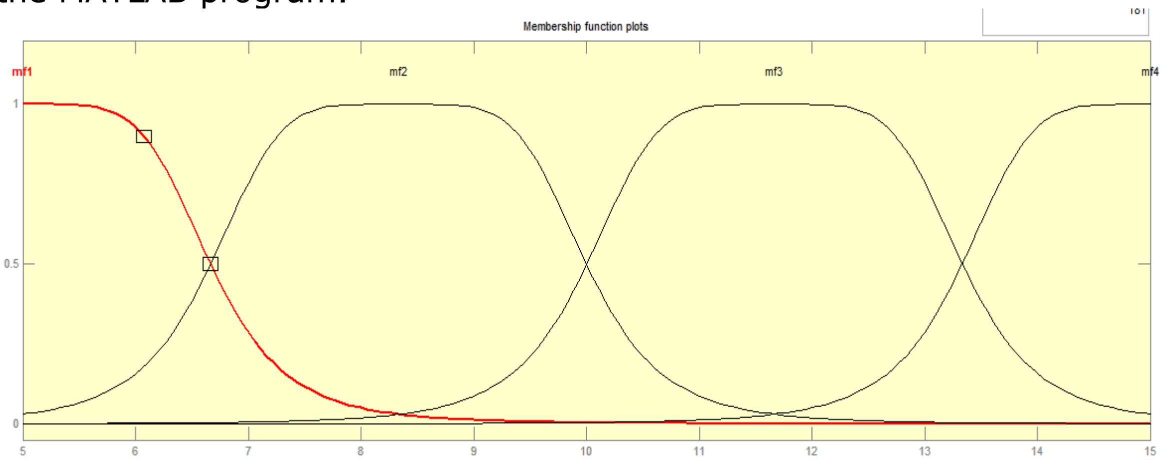

Figure 3. Flow membership functions.

The second of the input sets of membership functions is the return rate. As shown in Figure 4, the values and ranges are processed into the fuzzy logic module of the MATLAB program.

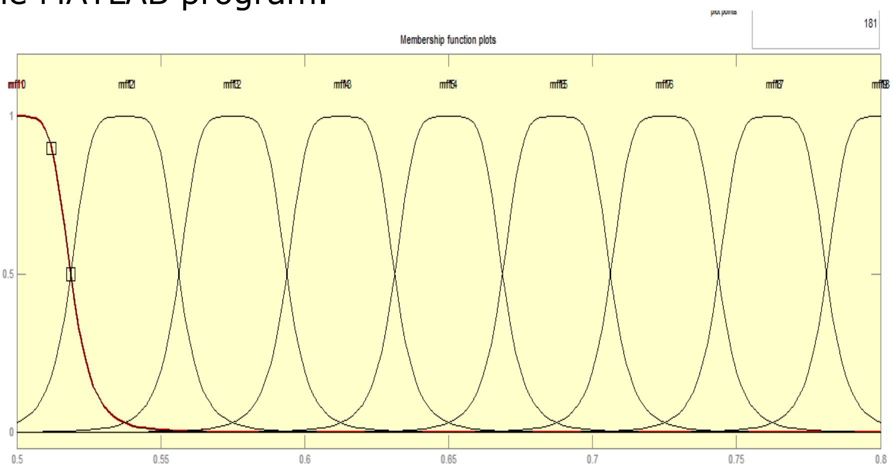

Figure 4. Return rate membership functions

Output Moisture is given as a set of membership functions. As shown in Figure 5, the values and ranges are processed into the fuzzy logic module of the MATLAB program.

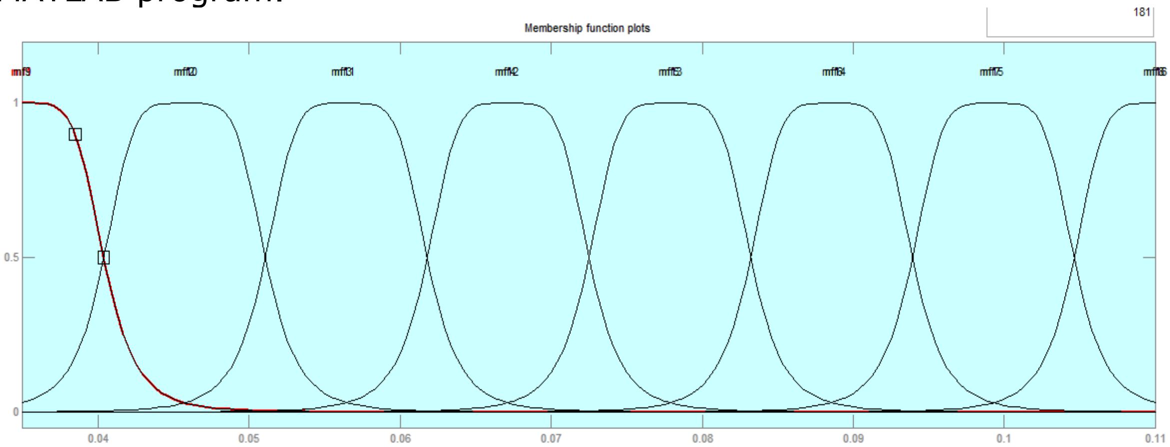

Figure 5. Humidity membership functions.

Second output Fuel is given as a set of membership functions. As shown in Figure 6, the values and ranges are processed into the fuzzy logic module of the MATLAB program.

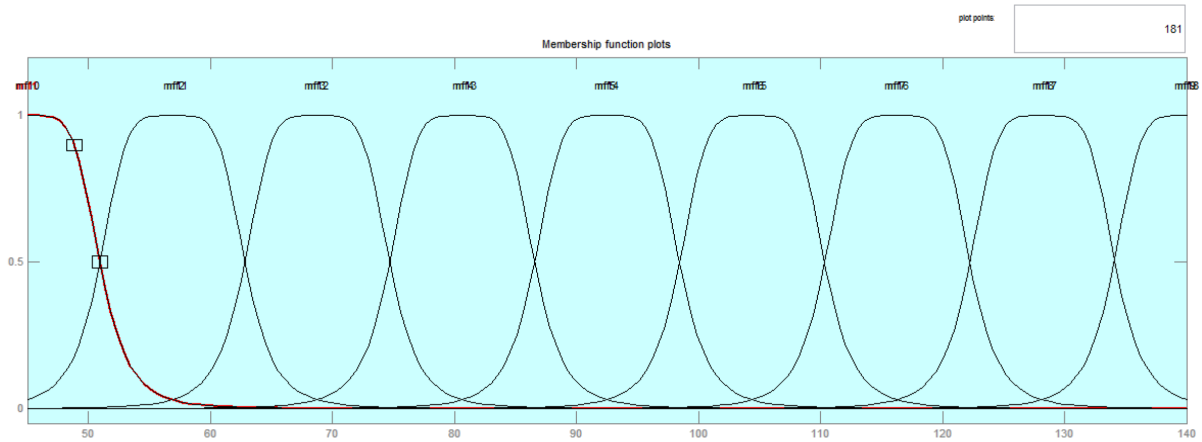

Figure 6. Fuel membership functions.

The rule table for humidity and fuel from the output functions is given in Figure 7 and Figure 8.

Figure 7. Rule table for humidity

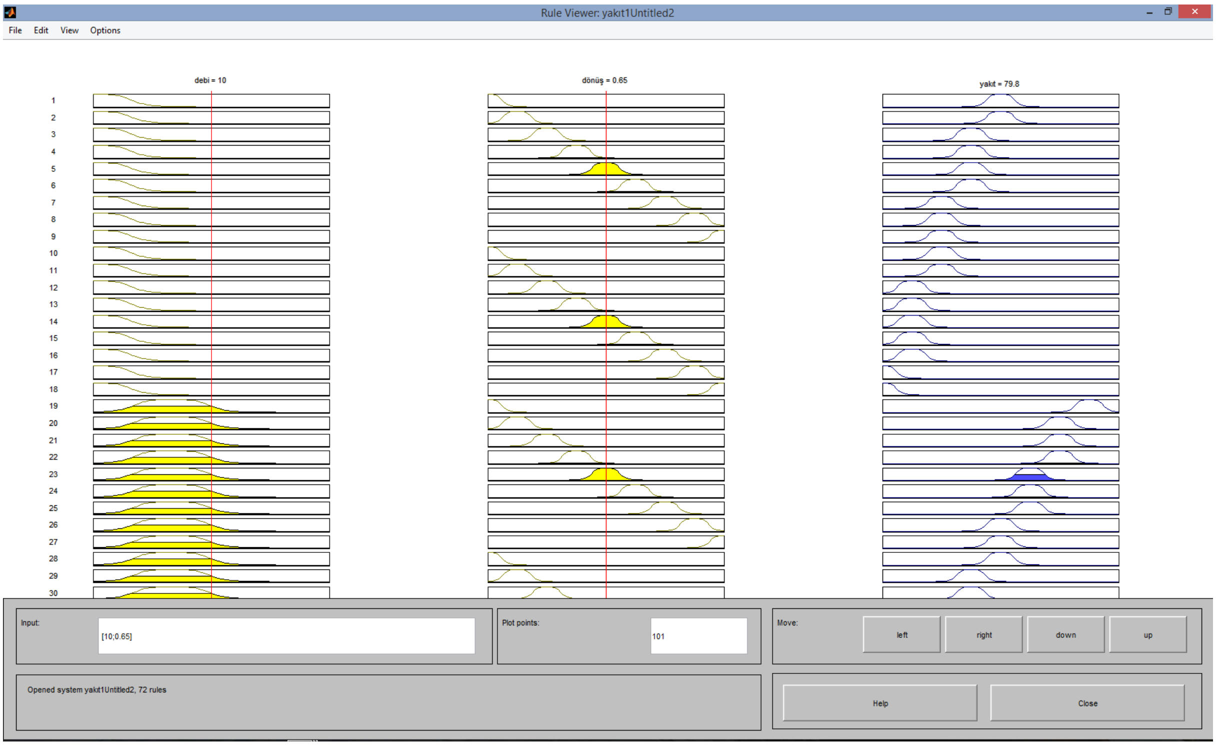

Figure 8. Rule table for fuel

In the study, the Generalized Bell Membership Function (GBellMF) method was selected for the membership functions in the input and output sets. This method results in a trapezoidal geometric shape, which allows for approximate values within the framework of fuzzy logic rules. A total of three hundred fuzzy rules were created. After entering the membership functions into the MATLAB fuzzy logic editor, the values of the membership functions were also inputted into the rule editor. Once the rule entries were completed, the results were observed using the rule viewer tool. The centroid method was chosen as the defuzzification method during the result generation process. After processing all the data, the simulation of the heat recovery system was performed using the MATLAB program.

3. Results and Discussion

Increasing the return air ratio reduces the required temperature lift of the burner by reusing already heated exhaust air. This directly decreases the specific fuel demand of the system. Higher airflow enhances convective mass transfer; however, excessive airflow increases thermal losses, which explains the observed optimum region rather than a monotonic improvement.

This study modeled the effects of air flow rate and return rate on fuel consumption and outlet humidity using fuzzy logic in the stenter machine. The results showed that fuzzy logic modeling can be successfully used in uncertain and nonlinear systems. Future studies may investigate the applicability of fuzzy logic modeling on different textile machines and under different production conditions. Figure 9 Humidity change graph before HR is given.

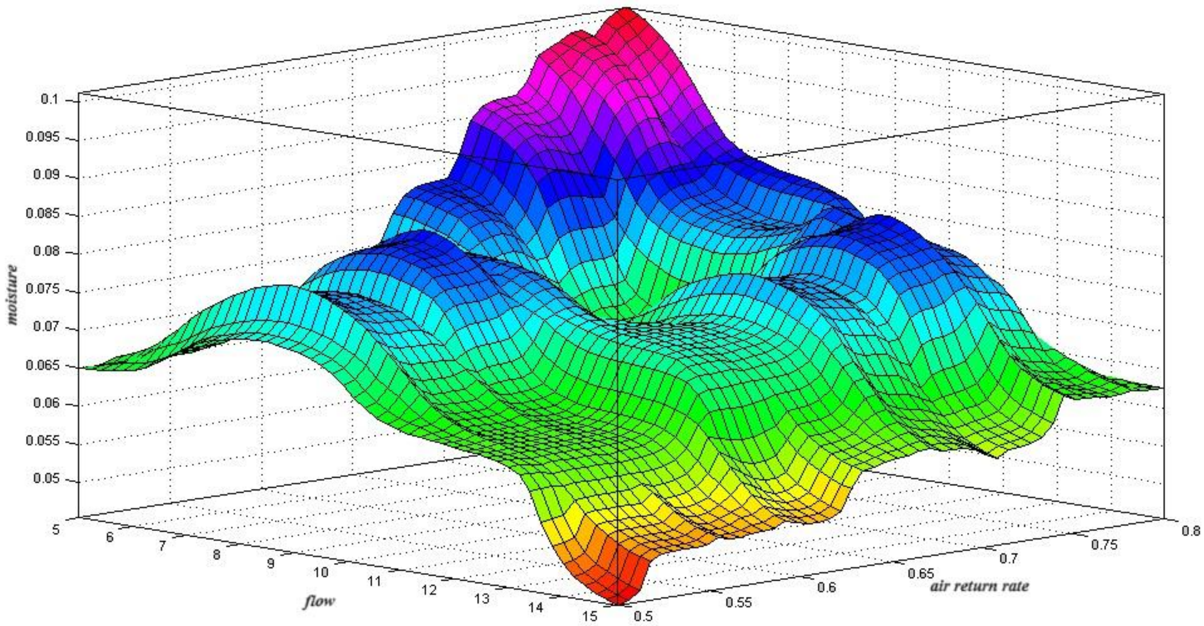

Figure 9. Graph of humidity change before HR

The provided graph illustrates the moisture content of the hot air exiting a stenter machine before heat recovery and how the return ratio of this air can be adjusted. A stenter machine is used in a drying process where hot air contacts the textile product, absorbing water vapor from the product and then exhausting it. In this process, the moisture content of the waste air indicates how much of the air's moisture-holding capacity is utilized. In the graph, the flow rate (in m^3/s) (X-axis) and the return ratio (in %) (Y-axis) effect on the moisture content (Z-axis) is shown as a three-dimensional surface. Low Flow Rate and Low Return Ratio: In this case, the moisture content is generally low. A low return ratio indicates that more fresh air is used, and therefore, the moisture content is low.

High Flow Rate and High Return Ratio: In this scenario, the moisture content is generally high. A high return ratio indicates that more waste air is reused, and therefore, the moisture content is high. Optimal Moisture Level: The graph can be used to determine the optimal moisture level for specific flow rates and return ratios. Energy Efficiency: A high return ratio can increase energy efficiency, but excessive moisture can slow down mass transfer and increase the risk of condensation. Therefore, the return ratio must be carefully adjusted. Control Mechanisms: By using dampers at the waste air outlets, the amount of air to be exhausted and reused can be adjusted. This is important for optimizing the system's efficiency. Based on this information, the graph can be used to optimize the operating conditions of the stenter machine. Figure 10 shows the moisture change graph after heat recovery.

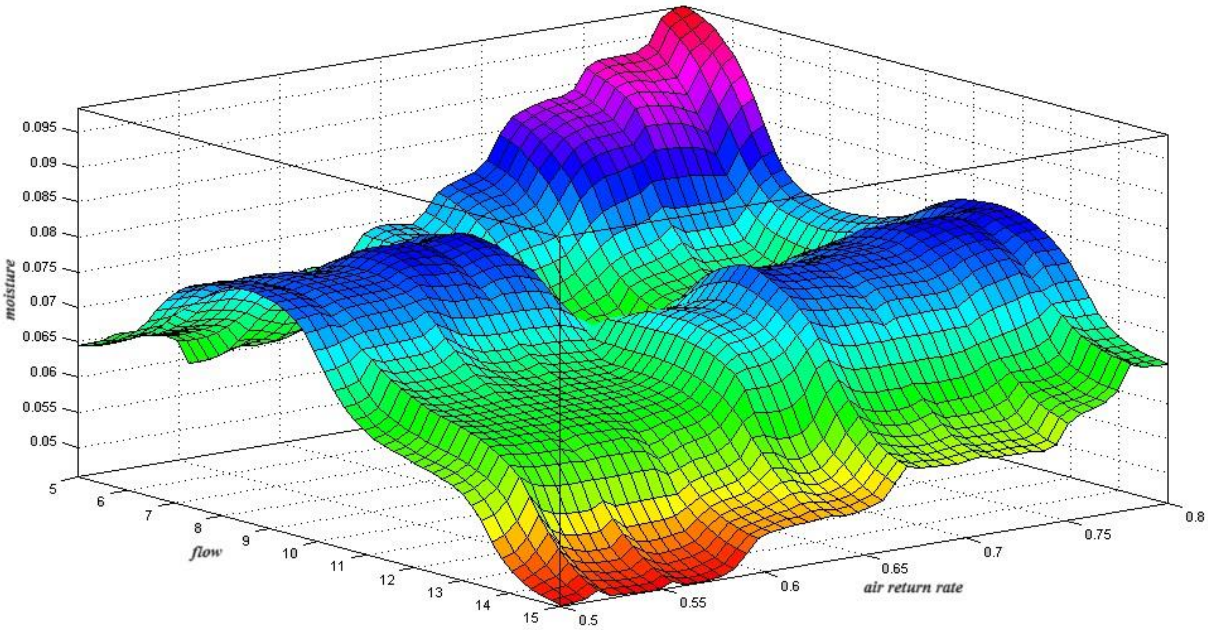

Figure 10. Graph of humidity change after HR

Figure 10 shows the relationship between outlet moisture and air flow rate in a stenter machine after heat recovery. The graph is depicted as a three-dimensional surface with the following axes: X-Axis (Flow Rate): Represents the air flow rate (in m^3/s). Y-Axis (Return Ratio): Represents the return ratio of the air (in %). Z-Axis (Moisture): Represents the amount of moisture in the air. Low Flow Rate and Low Return Ratio: In this region, the moisture content is observed to be low. This condition indicates that a low return ratio means more fresh air is used, and therefore, the moisture content is low. However, a low return ratio may lead to higher energy consumption, as more cold air needs to be heated. High Flow Rate and High Return Ratio: In this region, the moisture content is generally higher. A high return ratio indicates that more waste air is reused, resulting in higher moisture content. A high return ratio can improve energy efficiency, as less fresh air needs to be heated, but it may also lead to increased risks of condensation and slower mass transfer. Medium Flow Rate and Return Ratio: The graph shows that the moisture content can vary at medium levels of flow rate and return ratio. At these levels, a balance can be found to achieve both energy efficiency and appropriate moisture levels. Energy Consumption and Efficiency: As the return air ratio increases, energy efficiency can improve because less fresh air needs to be heated. However, a high moisture level may slow down mass transfer and increase the risk of condensation, which can negatively affect system performance. Optimal Setting: The graph can be used to determine the optimal moisture level for different flow rates and return ratios. Heat recovery systems aim to minimize energy consumption by carefully adjusting the return air ratio and flow rate. Control Mechanisms: The air flow rate and return ratio can be adjusted using the dampers at the waste air outlets. This adjustment is essential for optimizing the system's efficiency and performance. This graph can be used to analyze the effect of return air rate and airflow on fuel consumption prior to heat recovery and can help determine the optimal operating conditions of the system.

Overall, the relationship between air flow rate and return air ratio plays a critical role in determining the exit moisture content. Such graphs are useful for determining the optimal operating conditions of a Stenter machine in terms of energy savings and efficiency. The provided text and graph give insights into how the moisture content of the hot air exiting a Stenter machine and the return ratio of this air can be adjusted. The Stenter machine is used in a drying process where hot air contacts the textile product and removes water vapor from the product. In this process, the moisture content of the exhaust air indicates how much of the air's moisture-holding capacity is utilized. Figure 11 shows the relationship between flow rate and return air ratio in terms of fuel change before heat recovery.

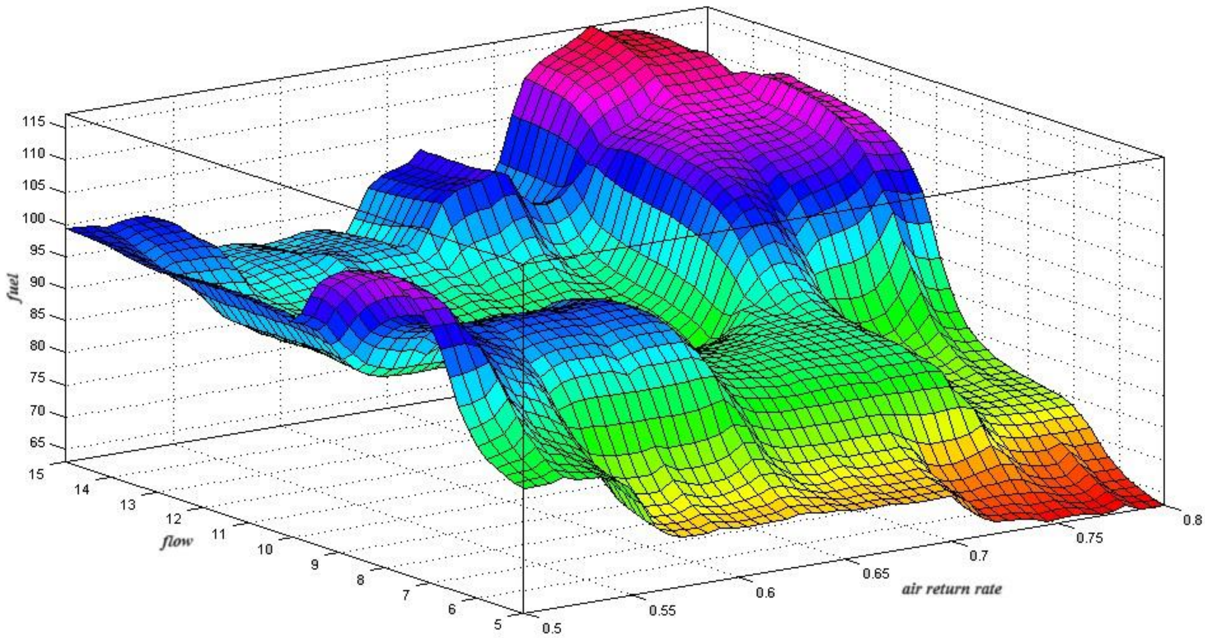

Figure 11. Fuel change before HR

The reduction in fuel consumption shown in Figure 11 resulted in an energy gain of 18% when the return rate reached 0.8%. This situation reveals the decision support potential of the fuzzy model in terms of energy management. The given graph illustrates the effect of different air flow rates and return air ratios on fuel consumption before heat recovery using a three-dimensional surface plot. One of the horizontal axes represents air flow rate (flow), the other horizontal axis represents return air ratio (return), and the vertical axis shows fuel consumption.

Relationship Between Flow Rate and Fuel Consumption: At low air flow rates (approximately 5-7 units), fuel consumption tends to be relatively higher. As the flow rate increases (approximately 8-14 units), there is generally a decrease in fuel consumption. However, this decrease may not be consistent with every increase in flow rate; some points may show increases in fuel consumption. Relationship Between Return Air Ratio and Fuel Consumption: At low return air ratios (around 0.5), fuel consumption remains high. As the return air ratio increases (ranging from 0.6 to 0.8), a noticeable decrease in fuel consumption is observed. Effects of Combinations: The combined effect of both flow rate and return air ratio on fuel consumption creates a more complex pattern. For example, high flow rates (12-14 units) combined with high return air ratios (0.7-0.8) result in the lowest levels of fuel consumption. Conversely, combinations of low flow rates and low return air ratios lead to the highest levels of fuel consumption.

In conclusion, the data from the graph indicate that significant savings in fuel consumption can be achieved by optimizing air flow rate and return air ratio. Particularly, combinations of high flow rates and high return air ratios are observed to minimize fuel consumption. Such analyses play a crucial role in energy efficiency studies and contribute to reducing operational costs.

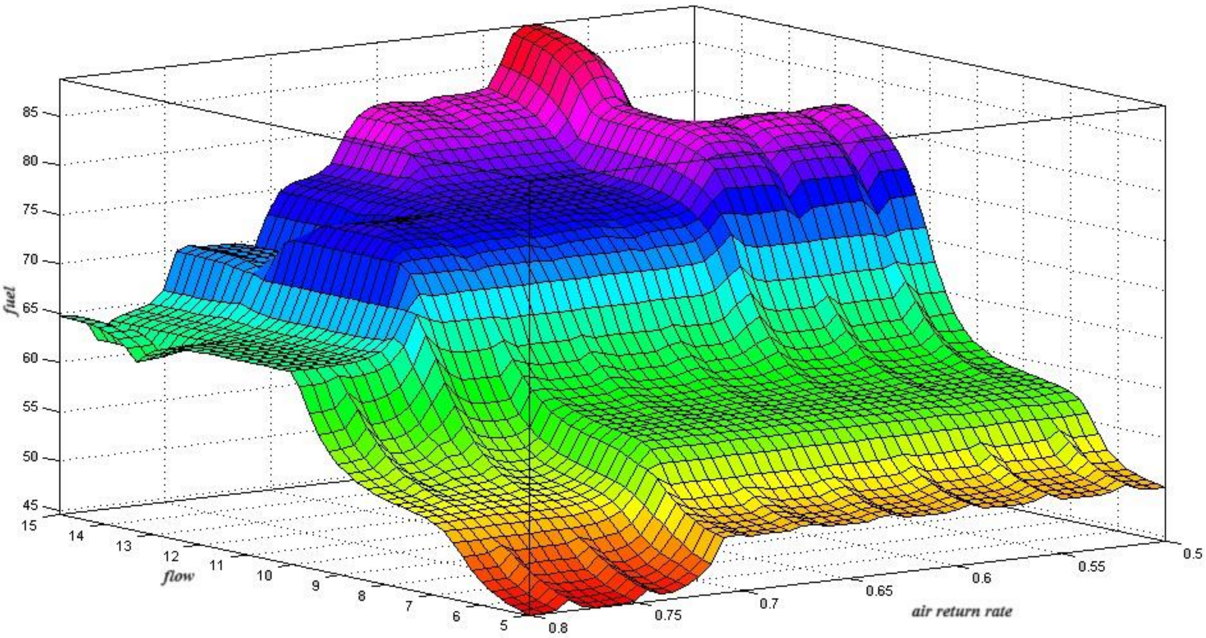

Figure 12. Fuel change after HR

Figure 12 shows the effect of different air flow rates and return air ratios on fuel consumption after heat recovery with a three-dimensional surface graph. One of the horizontal axes refers to the air flow rate (flow rate), the other horizontal axis refers to the return air rate (return), while the vertical axis shows the fuel consumption.

Flow Rate and Fuel Consumption Relationship: When the air flow rate is at low values (approximately 5-7 units), fuel consumption is relatively higher. As the flow rate increases (approximately 8-14 units), there is generally a decrease in fuel consumption. However, this decrease may not be consistent with every increase in flow rate; some points may show increases instead. Return Air Ratio and Fuel Consumption Relationship: At low return air ratios (around 0.5), fuel consumption remains high. As the return air ratio increases (within the range of 0.6-0.8), a significant decrease in fuel consumption is observed. Effect of Combinations: Evaluating both flow rate and return air ratio together creates a more complex effect on fuel consumption. For instance, combinations of high flow rate (12-14) and high return air ratio (0.7-0.8) result in the lowest levels of fuel consumption. Conversely, combinations of low flow rate and low return air ratio lead to the highest levels of fuel consumption.

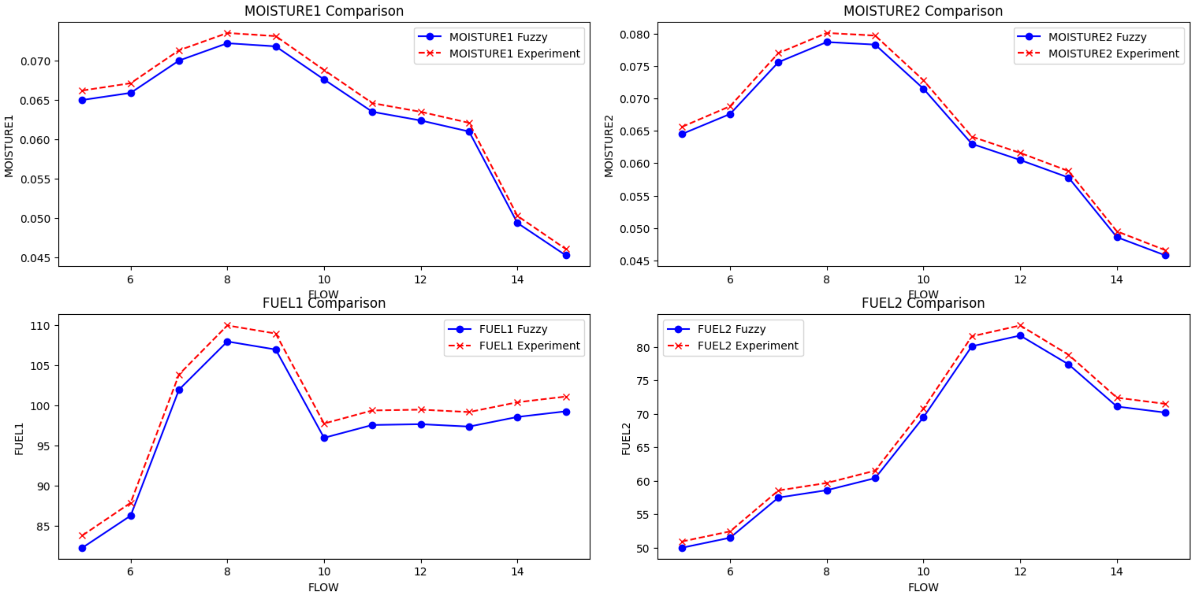

Figure 13. Comparison of fuzzy and experimental results before and after HR when the flow rate value was 0.5

Figure 13 Comparison of Fuzzy and Experimental Results Before and After HR for Flow Value 0.5 :

MOISTURE1 Comparison (Top Left): Both the fuzzy logic model and experimental data show that MOISTURE1 increases with FLOW until approximately FLOW 10, after which it decreases. Despite small differences between the fuzzy model and experimental data, the overall trends are quite consistent. Between FLOW 8 and 12, the fuzzy model's predictions closely match the experimental data, indicating that the fuzzy logic model accurately predicts the MOISTURE1 parameter. At around FLOW 6, the fuzzy model’s estimate is slightly higher, but this discrepancy is minor and acceptable. At FLOW 14, while experimental data show a slight decrease, the fuzzy model accurately predicts a similar decline.

MOISTURE2 Comparison (Top Right): MOISTURE2 increases with FLOW and peaks around FLOW 10 before decreasing. The fuzzy model provides results that are highly consistent with the experimental data. Data points between FLOW 6 and 14 show that the model and experimental data are very close. At FLOW 10, both data sets reach a peak, demonstrating high accuracy of the model. At FLOW 14, the model and experimental data show a similar decrease, indicating the model’s validity.

FUEL1 Comparison (Bottom Left): FUEL1 increases up to FLOW 10 and then decreases. The fuzzy model is generally consistent with experimental data but shows minor deviations at some points. The increasing trend between FLOW 6 and 10 is evident in both data sets. Around FLOW 8, the fuzzy model predicts slightly higher values, but this deviation is small and generally acceptable. Between FLOW 12 and 14, both data sets show similar trends.

FUEL2 Comparison (Bottom Right): FUEL2 increases with FLOW and peaks around FLOW 12, then slightly decreases. The fuzzy model aligns closely with experimental data. Data points between FLOW 6 and 12 show significant similarity between the model and experimental results. At FLOW 12, both data sets reach a peak, confirming the model’s accuracy. At FLOW 14, both the model and experimental data show a similar decrease.

The performance of the fuzzy logic model is quite successful when compared to experimental data for the four parameters (MOISTURE1, MOISTURE2, FUEL1, FUEL2). The model accurately predicts the general trends and provides acceptable results even with minor deviations in data points. This demonstrates that the fuzzy logic model can make accurate and reliable predictions. The fuzzy logic model demonstrated high correlation with experimental data across all tested scenarios, with a mean absolute error of 1.86%, indicating the model's reliability in predicting outlet moisture and fuel consumption under varying airflow and return ratio conditions.

Based on these graphs, we can make a positive assessment of the model’s performance and affirm its validity. Despite some minor deviations, the model's ability to accurately predict general trends shows that it is applicable in practical scenarios.

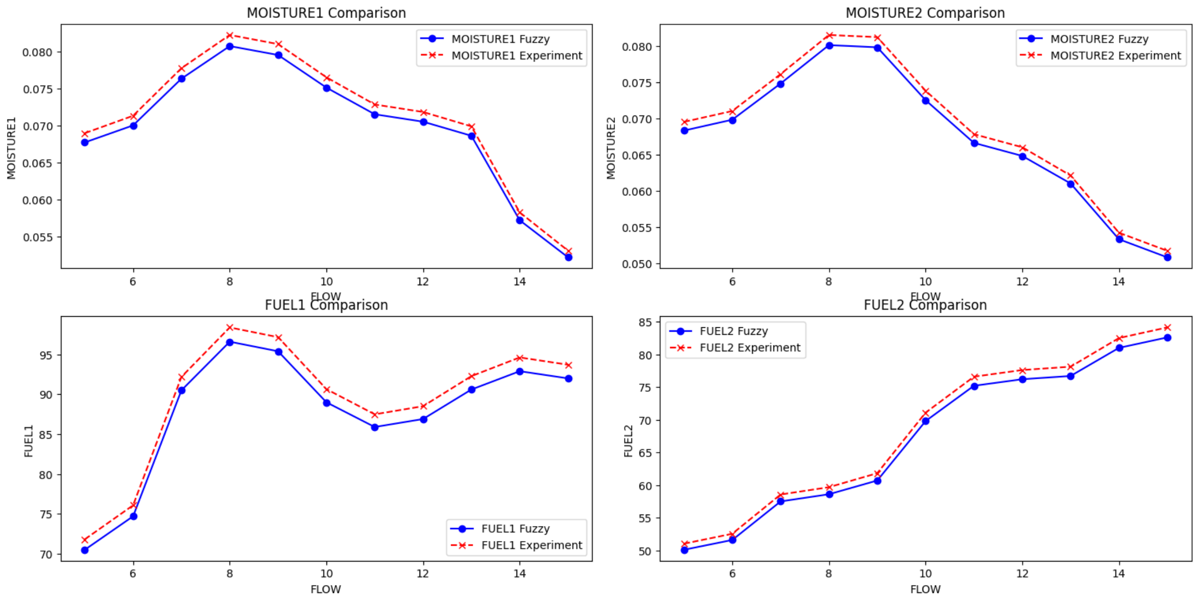

Figure 14. Comparison of Fuzzy and Experimental Results Before and After HR for Flow Value 0.6

Figure 14 illustrates the comparison of fuzzy and experimental results before and after HR with a flow value of 0.6 :

MOISTURE1 Comparison (Top Left): MOISTURE1 increases up to FLOW 8, peaks around FLOW 10, and then decreases. The fuzzy model aligns well with experimental data. In the FLOW 6-12 range, the fuzzy model and experimental data show nearly identical values. After FLOW 12, both data sets exhibit a decreasing trend, but the experimental data start from a slightly higher initial level. Around FLOW 8 and FLOW 10, both the fuzzy model and experimental data reach a peak and then decrease similarly.

MOISTURE2 Comparison (Top Right): MOISTURE2 increases between FLOW 8 and 10 and then decreases. The fuzzy model is very consistent with experimental data. In the FLOW 6-14 range, both data sets display similar trends. Around FLOW 10, both data sets peak, demonstrating the model's accuracy. At FLOW 14, both the model and experimental data show a similar decrease.

FUEL1 Comparison (Bottom Left): FUEL1 increases up to FLOW 8-10 and then decreases. The fuzzy model is generally consistent with experimental data, though some small deviations are observed. The increasing trend between FLOW 6 and 12 is evident in both data sets. Around FLOW 8, the fuzzy model predicts slightly higher values, but this deviation is small and generally acceptable. Between FLOW 12 and 14, both data sets show similar trends.

FUEL2 Comparison (Bottom Right): FUEL2 shows an increasing trend with FLOW, peaks around FLOW 12, and then slightly decreases. The fuzzy model is highly consistent with experimental data. Data points between FLOW 6 and 14 show significant similarity between the model and experimental results. At FLOW 12, both data sets peak, confirming the model’s accuracy. At FLOW 14, the model and experimental data exhibit a similar decrease.

The fuzzy logic model is quite successful when compared with experimental data for the four parameters (MOISTURE1, MOISTURE2, FUEL1, FUEL2). The model accurately predicts general trends and provides acceptable results even with minor deviations in data points. This demonstrates that the fuzzy logic model can make accurate and reliable predictions.

Based on these graphs, a positive assessment of the model's performance can be made, and its validity can be affirmed. Despite some minor deviations, the model's ability to accurately predict general trends shows that it is applicable in practical scenarios.

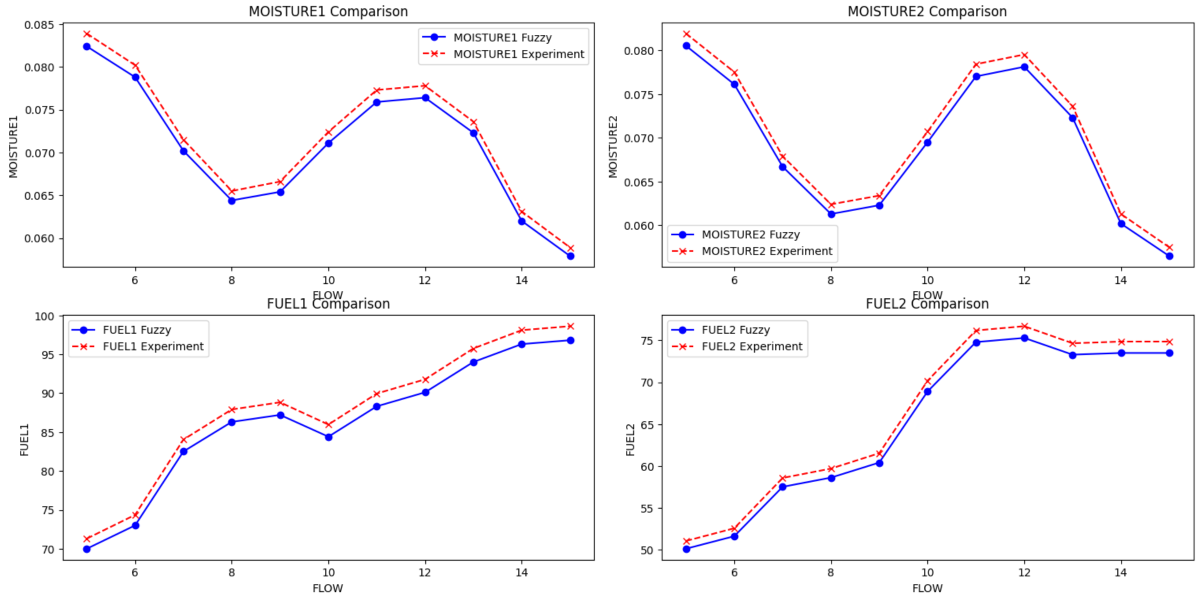

Figure 15. Comparison of Fuzzy and Experimental Results Before and After HR for Flow Value 0.7

Figure 15 shows the comparison of fuzzy and experimental results before and after HR with a flow value of 0.7:

MOISTURE1 Comparison (Top Left): MOISTURE1 peaks around FLOW 6, decreases up to FLOW 10, and then increases again up to FLOW 14. The fuzzy model and experimental data generally exhibit similar trends. Both data sets show a high value at FLOW 6, followed by a similar decreasing trend. After FLOW 10, both sets show an increasing trend. At around FLOW 8, the difference between the fuzzy model and experimental data is minimal. At FLOW 14, the fuzzy model and experimental data are quite compatible.

MOISTURE2 Comparison (Top Right): MOISTURE2 peaks around FLOW 6, decreases up to FLOW 10, then increases up to FLOW 12, and decreases again. The fuzzy model is very consistent with the experimental data. In the FLOW 6-14 range, both data sets exhibit similar trends. Around FLOW 8, the fuzzy model and experimental data show nearly identical values. Both data sets peak at FLOW 12 and then decrease.

FUEL1 Comparison (Bottom Left): FUEL1 increases between FLOW 6 and 10, then decreases. The fuzzy model and experimental data show generally similar trends. Both data sets increase between FLOW 6 and 12. After FLOW 12, both sets display a similar decreasing trend. Between FLOW 8 and 10, the fuzzy model and experimental data are very close in values. Between FLOW 12 and 14, both data sets follow a similar decreasing trend.

FUEL2 Comparison (Bottom Right): FUEL2 increases between FLOW 6 and 12, then remains constant. The fuzzy model and experimental data generally display similar trends. In the FLOW 6-14 range, both data sets show similar increase and stabilization trends. Between FLOW 8 and 10, the fuzzy model and experimental data are quite consistent. Between FLOW 12 and 14, both sets show a constant value.

The fuzzy logic model performs quite successfully when compared with experimental data for the four parameters (MOISTURE1, MOISTURE2, FUEL1, FUEL2). The model accurately predicts general trends and provides acceptable results even with minor deviations in data points. This demonstrates that the fuzzy logic model can make accurate and reliable predictions.

Based on these graphs, a positive assessment of the model's performance can be made, and its validity can be affirmed. Despite some minor deviations, the model’s ability to accurately predict general trends shows that it is applicable in practical scenarios.

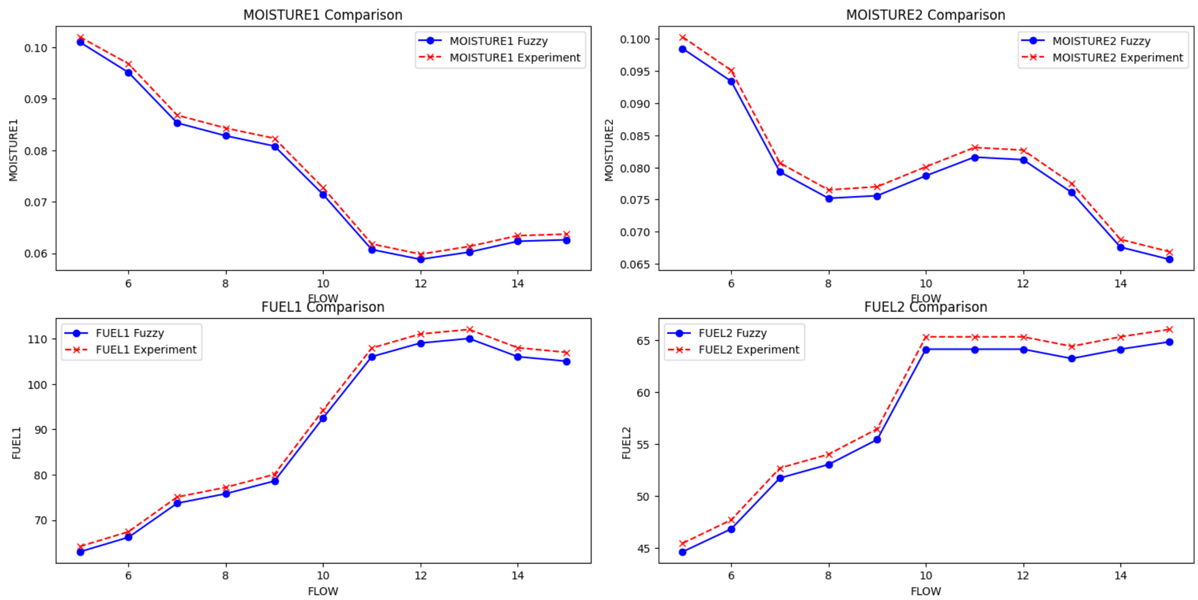

Figure 16. Comparison of Fuzzy and Experimental Results Before and After HR for Flow Value 0.8

Figure 16 shows the comparison of fuzzy and experimental results before and after HR with a flow value of 0.8. It compares fuzzy logic (Fuzzy) and experimental (Experiment) results for MOISTURE1, MOISTURE2, FUEL1, and FUEL2 parameters according to FLOW values. Detailed explanations for each parameter are as follows:

MOISTURE1 Comparison (Top Left): MOISTURE1 increases from FLOW 6 to 8, then shows a slight decrease up to FLOW 10, and increases again up to FLOW

14. The fuzzy model (blue) and experimental data (red) are quite consistent in terms of general trends. Particularly, around FLOW 8 and 10, both data sets show similar values. Both data sets exhibit similar increases between FLOW 6 and 8, and similar increases between FLOW 12 and 14.

MOISTURE2 Comparison (Top Right): MOISTURE2 increases from FLOW 6 to 8, shows a slight decrease up to FLOW 10, then increases again up to FLOW 12, and decreases up to FLOW 14. The fuzzy model (blue) and experimental data (red) are highly consistent in terms of general trends. Both data sets show similar values around FLOW 8 and 10. The trends are similar for increases between FLOW 6 and 8 and decreases between FLOW 12 and 14.

FUEL1 Comparison (Bottom Left): FUEL1 increases from FLOW 6 to 10, and then shows a decreasing trend up to FLOW 14. The fuzzy model (blue) and experimental data (red) are quite consistent in terms of general trends. Both data sets show similar values around FLOW 8 and 10, as well as similar increases between FLOW 6 and 8 and decreases between FLOW 12 and 14.

FUEL2 Comparison (Bottom Right): FUEL2 increases from FLOW 6 to 12, then remains constant up to FLOW 14. The fuzzy model (blue) and experimental data (red) are highly consistent in terms of general trends. Both data sets show similar values around FLOW 8 and 10, with similar increases between FLOW 6 and 8 and similar stabilization between FLOW 12 and 14.

In these graphs, the performance of the fuzzy logic model appears to be quite successful compared to the experimental data. Both data sets exhibit similar trends, and deviations are minimal. This indicates that the fuzzy logic model can make accurate and reliable predictions. The data in the graphs demonstrate that optimizing airflow and return air ratio can lead to significant savings in fuel consumption. In particular, combinations of high flow and high return air ratios are shown to minimize fuel consumption. Such analyses play an important role in energy efficiency studies and contribute to reducing operational costs. The reported values of energy savings in textile heat recovery systems vary between 10% and 25%, depending on the process configuration and the properties of the exhaust air (Hasanbeigi et al., 2012; Şekkeli & Keçecioğlu, 2012). The value of 18% fuel savings achieved in this study is within the expected range, thus verifying that the proposed modelling methodology yields realistic and feasible optimization results.

The results obtained using the developed fuzzy logic model were compared with experimental values. The satisfactory and precise prediction results indicate the effectiveness of the developed fuzzy logic model. The calculated mean absolute error of the fuzzy model is 1.86%. Thus, this fuzzy model has been proven to be both fast and reliable in predicting moisture and fuel amounts.

4. Conclusion

In this study, fuzzy logic modeling was applied to control airflow and humidity in the Stenter machine. The results obtained provide valuable insights into energy efficiency and waste air management. This approach could be a significant step towards energy savings and reducing environmental impacts in the textile industry. The model successfully predicted the effects of airflow and return ratio on fuel consumption and outlet moisture using fuzzy logic. It operated with high accuracy and helped in determining optimal conditions for energy efficiency.

When the flow value was 0.5, MOISTURE1 increased with FLOW up to 10 and then decreased. Both the fuzzy model and experimental data generally showed this trend consistently. MOISTURE2 reached a peak around FLOW 10 and then decreased, with high agreement between the fuzzy model and experimental data. FUEL1 increased up to FLOW 10 and then decreased; the fuzzy model provided results generally consistent with the experimental data. FUEL2 peaked around FLOW 12 and then slightly decreased, with good alignment between the fuzzy model and experimental data.

At a flow value of 0.6, MOISTURE1 increased up to FLOW 8, reached a peak around FLOW 10, and then decreased again. The fuzzy model was quite consistent with the experimental data for this parameter. MOISTURE2 increased between FLOW 8 and 10 and then decreased; the fuzzy model showed this trend very well in line with the experimental data. FUEL1 increased up to FLOW 10 and then decreased; the fuzzy model was generally consistent with the experimental data for this parameter. FUEL2 peaked around FLOW 12 and then slightly decreased, with good agreement between the fuzzy model and experimental data.

When the flow value was 0.7, MOISTURE1 peaked around FLOW 6, decreased up to FLOW 10, and then increased again up to FLOW 14. The fuzzy model and experimental data exhibited similar trends for this parameter. MOISTURE2 peaked around FLOW 6, decreased up to FLOW 10, then increased up to FLOW 12, and decreased again; the fuzzy model showed this trend quite consistently with the experimental data. FUEL1 increased between FLOW 6 and 10 and then decreased; the fuzzy model and experimental data exhibited similar trends. FUEL2 increased between FLOW 6 and 12 and then remained constant; the fuzzy model and experimental data generally showed similar trends.

At a flow value of 0.8, MOISTURE1 increased between FLOW 6 and 8, showed a slight decrease up to FLOW 10, and then increased again up to FLOW 14. Both the fuzzy model and experimental data showed this trend generally consistently. MOISTURE2 increased between FLOW 6 and 8, showed a slight decrease up to FLOW 10, then increased again up to FLOW 12, and decreased up to FLOW 14; the fuzzy model was quite consistent with the experimental data. FUEL1 increased between FLOW 6 and 10 and then decreased up to FLOW 14; the fuzzy model and experimental data exhibited similar trends. FUEL2 increased between FLOW 6 and 12 and then remained constant; the fuzzy model and experimental data generally showed similar trends.

The fuzzy logic model accurately predicted general trends for MOISTURE1, MOISTURE2, FUEL1, and FUEL2 parameters across all flow values (0.5, 0.6, 0.7, 0.8). Although minor deviations were observed at some points in the graphs, the overall trends were consistent and acceptable. The alignment of the fuzzy logic model with experimental data indicates that the model can make accurate and reliable predictions. These comparisons show that the developed fuzzy logic model is applicable in practical scenarios and accurately predicts general trends. The mean absolute error of 1.86% supports the high accuracy of the model.

Improvements achieved after HR contribute significantly to energy efficiency and savings goals. The use of the fuzzy logic model stands out as an effective tool for performance evaluation of such systems. Future work should involve broader studies to perform similar analyses on different systems. After HR, there was a notable improvement in energy savings by examining the relationship between fuel consumption, return ratio, and airflow. Similarly, the relationship between outlet moisture, return ratio, and airflow showed more efficient performance after HR. The fuzzy logic graphs clearly demonstrated increases in efficiency and reductions in energy consumption in both cases. The fuzzy logic model presented by the study is a viable decision support system for energy efficiency optimization in stenter machines. Similar approaches can be generalized to other industrial drying systems.

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