Numerical Simulation of Drying Equipment for Vegetal Matter with Automatic Process Control and Moisture Estimation by means of a Neural Network

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Abstract: *This study presents the development and validation of a comprehensive numerical simulation model for drying equipment designed for vegetal matter, utilizing automatic process control and moisture estimation through a neural network. The system, modeled in AMESim, includes a TLUD (Top-Lit UpDraft) gasifier as the heat source, an air flowrate regulation mechanism controlled by butterfly valves, and a drying chamber. A PID (Proportional-Integral-Derivative) controller with autotuning capabilities manages the air flowrate to maintain the desired drying temperature. Additionally, a neural network, trained with experimental data, estimates the relative moisture and mass of the drying leaves, achieving high training and validation fidelities of 99.99%. The simulation results highlight the effectiveness of the PID controller in stabilizing the drying environment and the neural network's accuracy in predicting moisture content. Also these demonstrate significant potential for optimizing drying processes in agricultural applications, enhancing both efficiency and product quality. Future research directions include expanding the dataset, exploring other machine learning algorithms, and integrating advanced sensor technologies for real-time data acquisition and process control.*

Keywords: *AMESim Numerical Simulation, Drying Equipment, Vegetal Matter, Automatic Process Control, Moisture Estimation, Neural Network, PID Controller*

1. Introduction

In the context of the deepening global energy and food crisis, the use of renewable energy in agricultural production processes, increasing energy independence from the national energy system, and enhancing the energy efficiency of processing equipment have become essential concerns for specialists in the field. The method of preserving plant products through enzymatic inactivation (dehydration) is considered by experts to be the most effective and healthiest long-term preservation method, ensuring food safety for consumers. Through dehydration, products significantly concentrate their nutritional and organoleptic properties, having a higher content of active principles compared to fresh products [1].
An important direction addressed in research on the dehydration preservation of vegetables and fruits involves the use of solar energy or energy obtained from other renewable sources in this process. It can be demonstrated that by using relatively simple equipment, the dehydration process can be conducted so that the final products are of the highest quality, and preservation costs are minimized [2].
Within INOE 2000-IHP, there have been concerns related to research-development-innovation-assimilation of new products and technologies, which will constitute progress for the Romanian manufacturing of convective dryers. At the same time, efforts have been made to create energy-independent equipment, in which the thermal energy required for the dehydration process is produced with the help of a 10 kW thermal generator operating on the TLUD principle, from locally available biomass. The air-to-air heat exchanger will provide a clean drying agent (hot air), with major implications on the quality of the products and for consumer health.
The automatic control of the drying process using a Top-Lit UpDraft (TLUD) device is an innovative technology that combines the principles of controlled combustion and efficient drying. A TLUD is a

gasifier that uses biomass to produce syngas and heat, commonly used in cooking or heating applications. In the context of drying plant materials, TLUDs can be integrated into an automatically controlled drying system.
Using this type of system, the process of dehydrating plant products follows a cycle diagram, correlated with the technology characteristic of each species, including the following phases, as shown in Figure 1 [3].

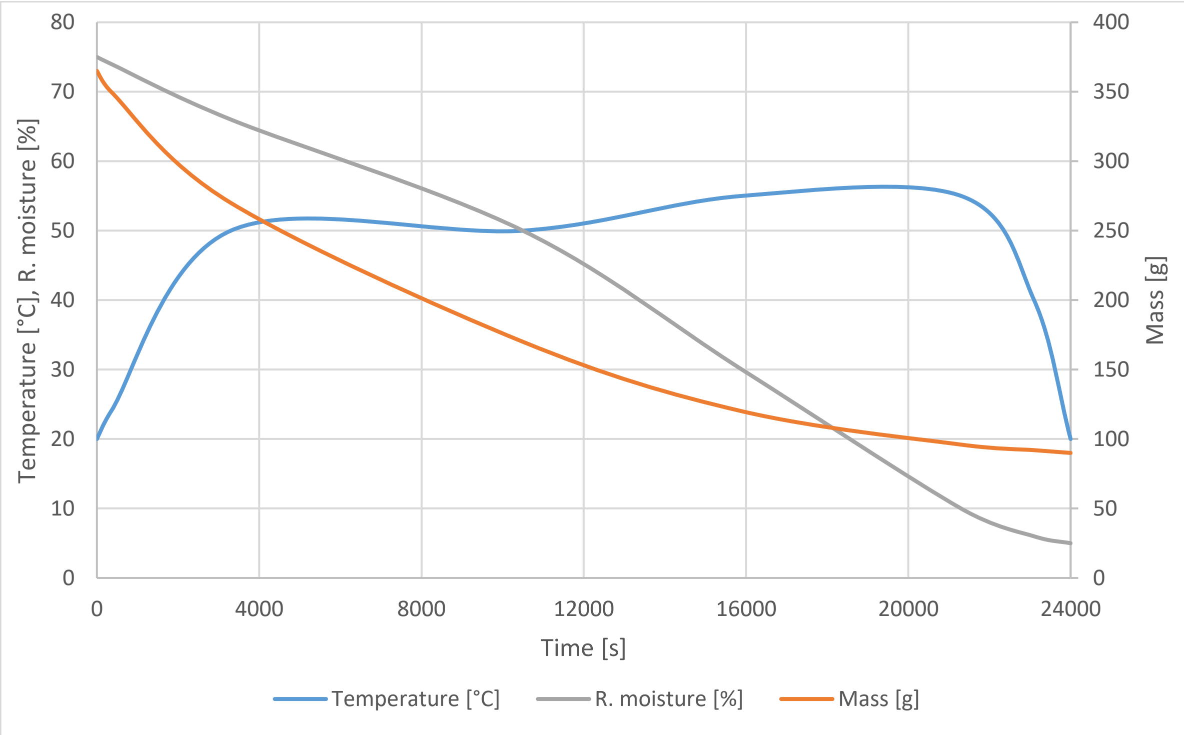


Fig. 1. Phases of the dehydration process

The ***Heating phase***, in which all thermal energy is transferred to the products, represents a critical stage in the dehydration process. To ensure efficient heat transfer to the products, the surrounding atmosphere must be saturated, or the partial pressure of water vapor on the surface of the products must equal the partial pressure of water vapor in the air. During this phase, the temperature of the products gradually increases until it approaches the temperature of the drying agent (hot air). For this reason, it is essential that the temperature during this phase does not exceed the threshold that could cause product deterioration [4].
The ***Conditioning phase*** is generally used for products at risk of crust formation or those with low external moisture, aiming to equalize moisture throughout the product to facilitate the drying process. In this stage, the temperature is kept constant, and moisture is regulated to produce controlled moistening of the products.
The ***Drying phase*** is the most crucial stage of the entire process. In this phase, water moves from areas of higher moisture content in the products to those with lower moisture content through diffusion. The evaporation of water from the surface of the products occurs at a certain rate, which must match the diffusion rate to prevent the phenomenon of surface hardening.
The ***Equalization phase*** is recommended for porous products dried in hot and humid periods. After the drying process is completed, the products undergo a low-moisture heat treatment to close the pores and prevent rehydration.
The ***Cooling phase*** generally occurs by expelling hot air through controlled dampers. If precise cooling is required, heating control is also practiced to maintain a gradient. Moisture is not controlled.
This paper presents the development and validation of a comprehensive numerical simulation model for drying equipment for plant raw materials (medicinal and aromatic plants), using automatic process control and moisture estimation through a neural network.

2. Material and Method

Figure 2 shows the testing scheme of the convective dryer [4]. The acquired parameters are: chamber temperature, primary air flowrate, and secondary air flowrate. The drying chamber temperature is measured using a Pt100 probe with a range of 0…200 °C. The 4…20 mA signals from the temperature converter and air flowmeters are coupled to the 0…10 V inputs of the acquisition board using 250 Ohm resistors connected to GND. The air flowmeters are used to monitor and regulate the primary and secondary air flowrates. A Proportional-Integral-Derivative (PID) control block from the LabView library is used to regulate the temperature. The PID controller output is monitored with two comparator blocks, and at two thresholds, positive and negative, of the controller signal variation, two digital outputs of the data acquisition board are commanded to extend or retract the actuator that controls the combustion gas flow from the TLUD generator. The actuator extension or retraction is achieved with two relays, one powering the actuator with polarity +/- and one powering the actuator with polarity -/+.

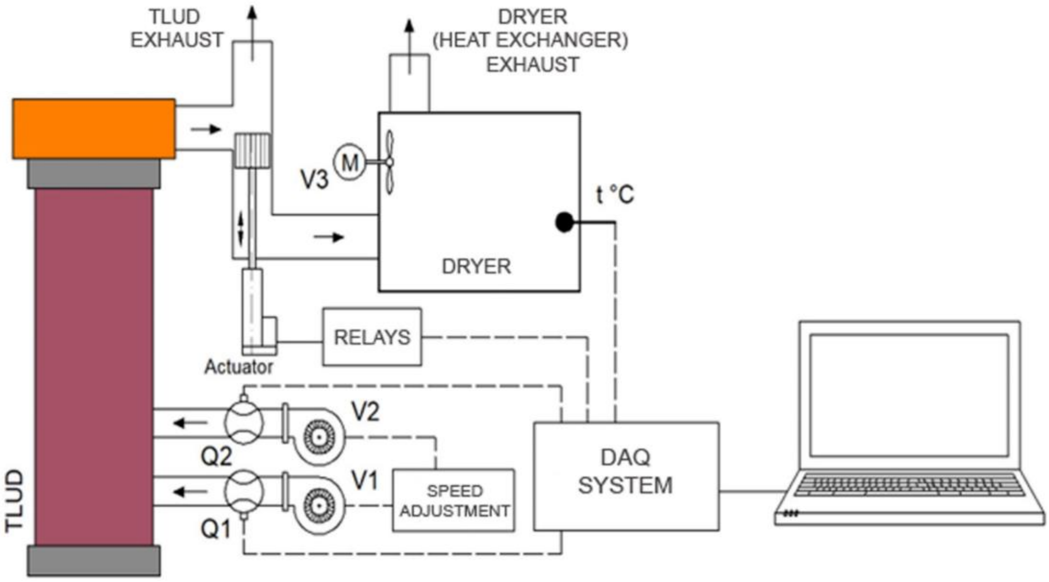


Fig. 2. Testing scheme of the convective dryer

The values of the monitored parameters can be tracked in real-time on the application panel, which allows for the plotting of diagrams for parameters that are interdependent, and the acquisition of data that reflects the evolution of the parameters over time, for preset intervals or for the entire operation cycle.
Laboratory tests focused on how the equipment achieves the technical and functional parameters imposed by the dehydration technology for mulberry leaves, which have medicinal properties in the treatment of diabetes [6].
The TLUD gasification reactor converts the energy of the biomass into thermal energy of the combustion gas-smoke mixture (resulting from the combustion of syngas, obtained in the gasification process). The heat transfer from this to the dehydration agent takes place in the heat exchanger located inside the dryer, at the level of its radiant surfaces [7 - 9].
The biomass is introduced into the reactor's fuel basket (2-3 cm below the syngas combustion air supply holes) and rests on a grate through which primary air for gasification passes from bottom to top. The solid fuel is ignited at the top of the load. Rapid pyrolysis creates a front of incandescence at the top and continues downward into the biomass in the reactor. Rapid pyrolysis results in syngas, tar, and biochar.
The tars pass through the incandescent charcoal layer, are cracked, and are completely reduced due to the heat radiated by the pyrolysis front and the flame located at the upper level. The resulting gas mixes with the secondary air introduced into the combustion zone through orifices at the top of the reactor. The high-turbulence mixture burns with a flame at temperatures around 900°C. Thermal power is regulated by varying the primary and secondary air flows.

The value of the hot air temperature in the drying chamber is determined by the position of the disc closing the combustion gas passage sections in the flowrate regulation device.

In this study, we developed a comprehensive numerical simulation model of a medicinal plants and fruit drying system using AMESim. The primary components of the system include a TLUD (Top-Lit UpDraft) type gasifier as a hot and dry air source, an air flowrate regulation device, and a drying chamber. The air flowrate regulation is managed by two butterfly valves with flaps with an offset of 90 degrees, which control the flowrate of hot air to the drying chamber. To maintain the prescribed temperature within the drying chamber, a PID controller is employed. This controller adjusts the air flowrate based on real-time temperature readings to compensate for variations in the gasifier's output temperature.

The TLUD gasifier serves as the heat source for the drying system, producing hot air through the combustion of biomass. The temperature output from the gasifier is inherently variable, necessitating a dynamic control mechanism to ensure a consistent drying environment. The PID controller is configured with autotuning capabilities, allowing it to adapt its parameters automatically for optimal performance. The autotuning feature is crucial for maintaining the desired temperature in the drying chamber, as it continuously adjusts to compensate for any deviations caused by fluctuations in the gasifier's temperature.

Additionally, a neural network is integrated into the simulation to estimate the relative moisture and mass of the drying leaves. This neural network is trained using experimental data on temperature and drying time to provide accurate predictions of the relative moisture content and mass loss of the leaves throughout the drying process. The neural network's architecture comprises six dense layers, each with 100 neurons and Rectified Linear Unit (ReLU) activation functions, trained using the stochastic gradient descent method. The training and validation fidelities of the neural network are both exceptionally high, at 99.99%, ensuring reliable and precise estimations. These estimations are crucial for monitoring and optimizing the drying process, ultimately improving the quality and efficiency of the dried product.

Figure 3 illustrates the overall structure of the drying equipment simulation model. It includes the key components such as the TLUD type gasifier, the heat source, the air flowrate regulation system, the drying chamber, the PID controller, and the neural network. The comprehensive network diagram helps in visualizing how each part of the system interacts and integrates within the simulation framework.

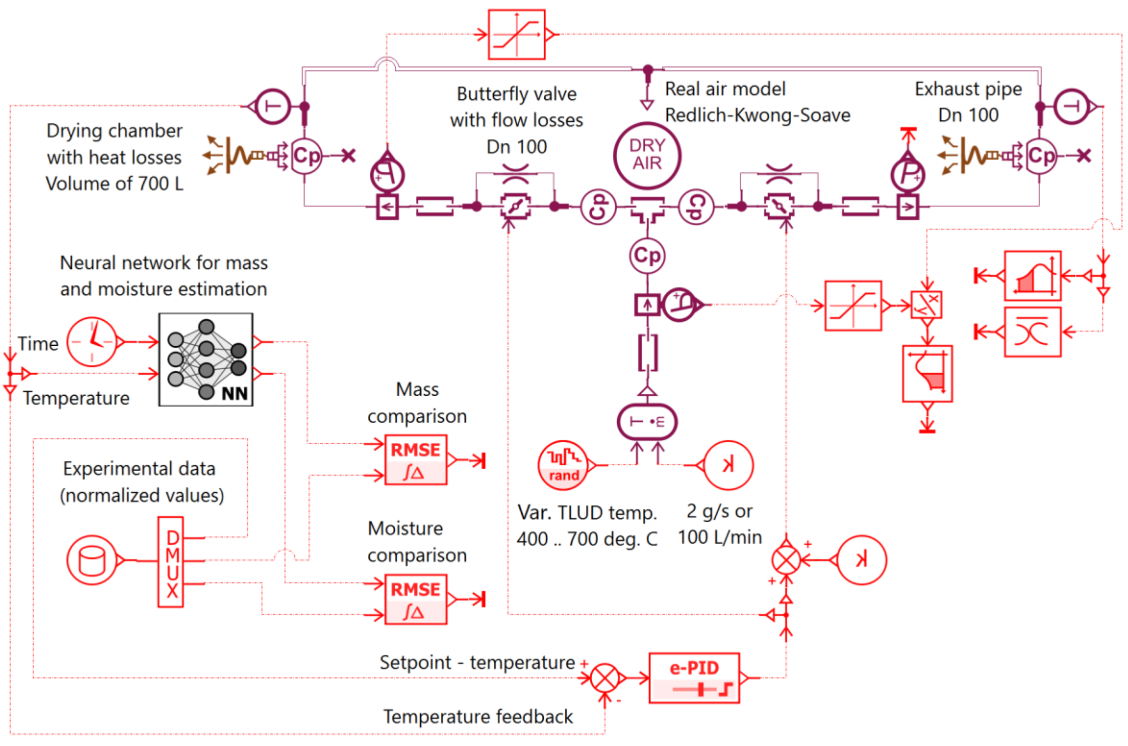
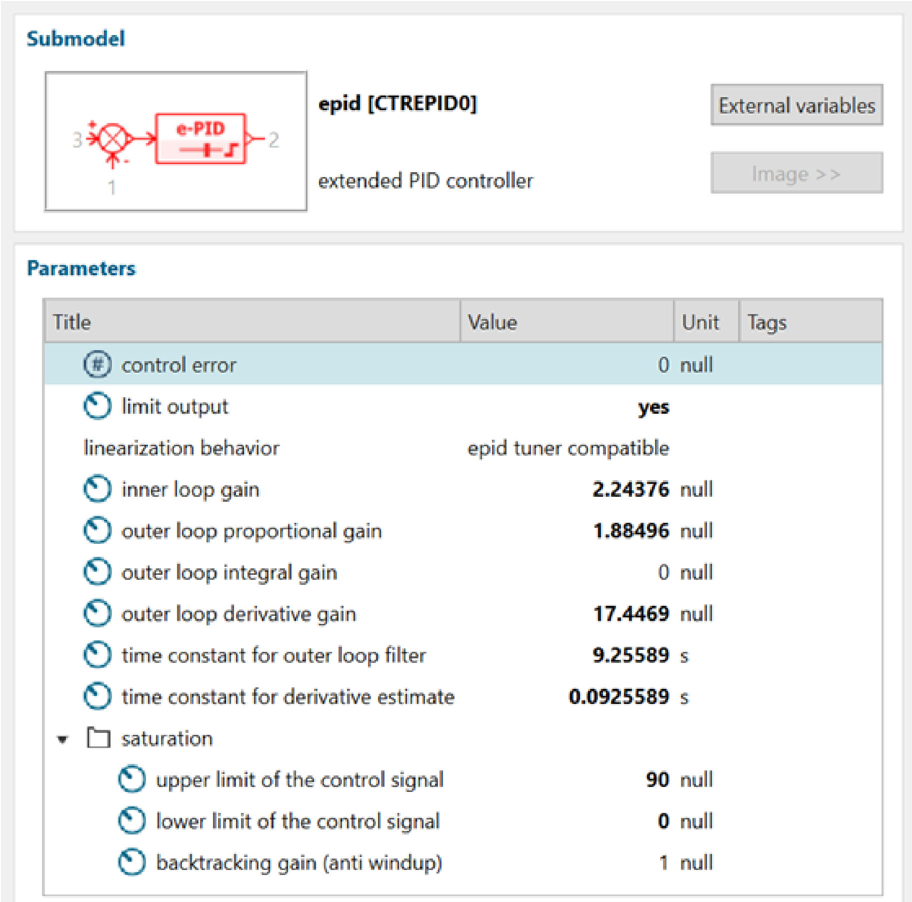


Fig. 3. Numerical simulation network of the drying equipment for vegetal matter with automatic process control and moisture estimation by means of a neural network

Figure 4 shows the parameters and configuration settings of the e-PID controller used in the simulation. Autotuning capabilities are highlighted, indicating that the controller can adjust its output to maintain optimal performance. The specific parameters shown would include gain settings, time constants and saturation settings, etc.



Title	Value	Unit	Tags
control error	0	null	
limit output	yes		
linearization behavior	epid tuner compatible		
inner loop gain	2.24376	null	
outer loop proportional gain	1.88496	null	
outer loop integral gain	0	null	
outer loop derivative gain	17.4469	null	
time constant for outer loop filter	9.25589	s	
time constant for derivative estimate	0.0925589	s	
saturation			
upper limit of the control signal	90	null	
lower limit of the control signal	0	null	
backtracking gain (anti windup)	1	null	

Fig. 4. Parameters of the e-PID controller with autotuning

Figure 5 details the architecture of the neural network used to estimate relative moisture and mass of mulberry leaves during the drying process. The diagram shows the input variables (time and temperature) and the output variables (mass and relative moisture), along with the layers and connections within the neural network.

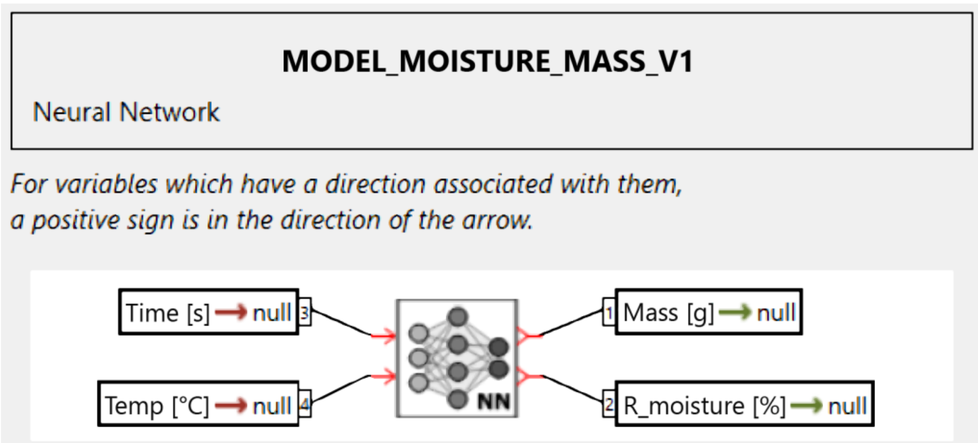


Fig. 5. Diagram of the neural network for estimating the relative moisture of mulberry leaves, with its inputs and outputs

Table 1 details the parameters of the neural network model used to estimate the relative moisture and mass of mulberry leaves during the drying process. The model, named "Model_moisture_mass_v1," is a static neural network featuring a total of six dense layers, each containing 100 neurons. The network employs ReLU activation functions across all layers, which helps in capturing non-linear relationships within the data. The neural network was trained using the stochastic gradient descent method, with a learning rate set at 0.0012 and a batch size of 16, ensuring efficient convergence during training. The model's training was conducted over 1,000 epochs, resulting in exceptionally high training and validation fidelities of 99.99%. The network benefits from adaptive learning and data shuffling, further enhancing its accuracy and generalization capabilities. The input variables for the network are time (in seconds) and temperature (in degrees Celsius), while the output variables are mass (in grams) and relative moisture (in percentage). The training process was completed in 32 seconds, underscoring the efficiency of the model setup.

Table 1: Neural network parameters

Model name	Model_moisture_mass_v1
Type of model	Static Neural Network
Training fidelity [%]	99.99
Validation fidelity [%]	99.99
Total trained epochs	1000
Number of layers	6
Layer types	6 x 'Dense'
Number of cells	6 x 100
Activation types	6 x 'ReLU'
Training method	Stochastic gradient descent
Learning rate	0.0012004999999999995
Batch size	16
Adaptive learning	True
Data shuffling	True
Input variables	['Time [s]' and 'Temp [C]']
Output variables	['Mass [g]' and 'R_moisture [%]']
Training duration [s]	32.0

3. Results and Discussions

Figure 6 shows the performance metrics of the neural network, specifically the training and validation errors for estimating the relative moisture and mass of the leaves. It demonstrates how well the neural network has been trained and validated, indicating its accuracy and reliability in the simulation.
Figure 6 provides a detailed visualization of the training and validation errors associated with the neural network used for estimating the relative moisture and mass of mulberry leaves during the drying process. This figure is crucial for assessing the performance and reliability of the neural network model implemented in the study.
Training and Validation Process - The neural network model comprises six dense layers, each with 100 neurons and ReLU activation functions, trained using the stochastic gradient descent method. The training process involved 1000 epochs, ensuring thorough learning and fine-tuning of the model parameters. The high training fidelity of 99.99% indicates that the model has effectively learned the underlying patterns and relationships within the training data.
Analysis of Errors - The figure illustrates the temporal evolution of both training and validation errors throughout the training process. The training error curve (depicted in blue) demonstrates a

rapid decrease during the initial epochs, followed by a gradual convergence to a minimal error level. This indicates that the model quickly learns the fundamental features of the data and then fine-tunes to minimize the error.
Similarly, the validation error curve (depicted in red) follows a comparable trend, showing a steady decline and eventual stabilization. The close alignment of the training and validation error curves suggests that the model generalizes well to unseen data, avoiding overfitting—a common issue in neural network training. The minimal gap between these curves further underscores the robustness of the model.
Implications for Model Performance - The exceptionally low values of both training and validation errors reflect the neural network's high accuracy in estimating the relative moisture and mass of the leaves under the drying process. This high fidelity is crucial for reliable real-time monitoring and control of the drying process. Accurate moisture estimation allows for better regulation of drying conditions, ultimately enhancing the quality and efficiency of the dried product.
Practical Significance - In practical terms, the neural network's performance, ensures that the drying system can maintain optimal conditions with minimal human intervention. The model's reliability in predicting key parameters enables more precise adjustments to the drying environment, leading to consistent product quality and reduced energy consumption. This is particularly important in agricultural applications, where variations in drying conditions can significantly impact the final product.
Figure 6 effectively demonstrates the neural network's capability to accurately model and predict the drying process's critical parameters. The low training and validation errors attest to the model's reliability and robustness, making it a valuable tool for optimizing the drying of vegetal matter. Future enhancements, such as incorporating additional data types and advanced sensor technologies, could further improve the model's accuracy and applicability in diverse drying scenarios.

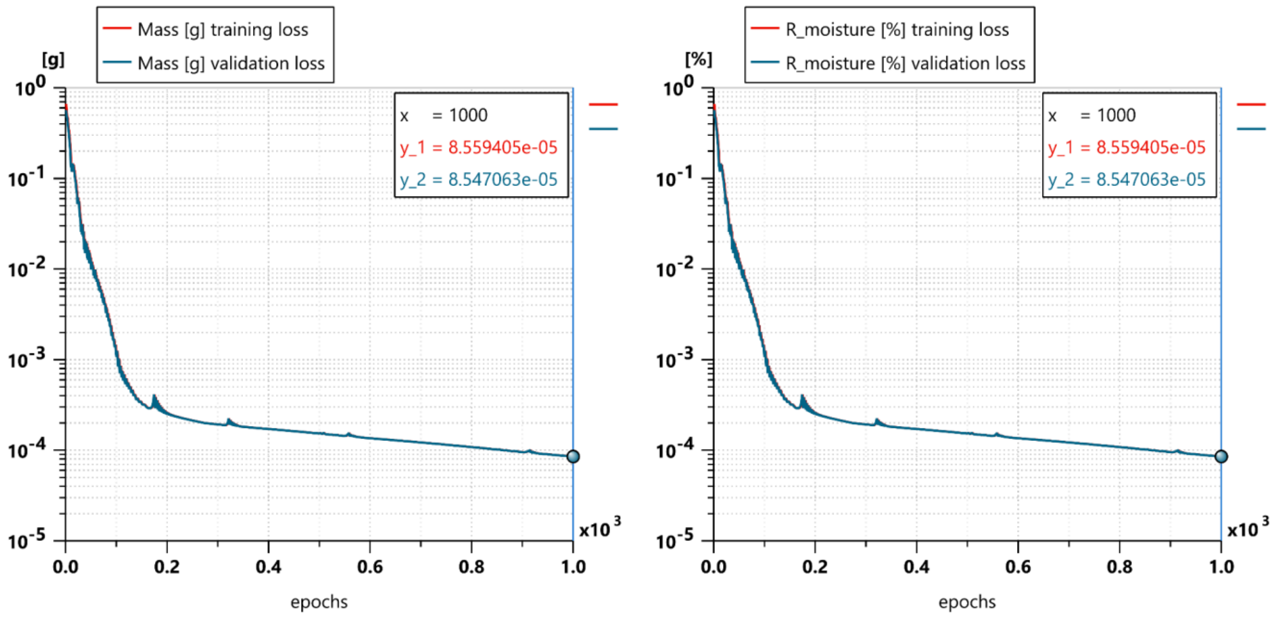


Fig. 6. The training and validation error of the neural network for the two estimated parameters (relative moisture and mass of mulberry leaves during drying cycle)

Figure 7 illustrates how the key parameters of the TLUD type gasifier, such as the outlet temperature, hot air flowrate and pressure, change over time. It highlights the dynamic behavior of the gasifier and the need for the PID controller to compensate for these variations to maintain consistent drying conditions.

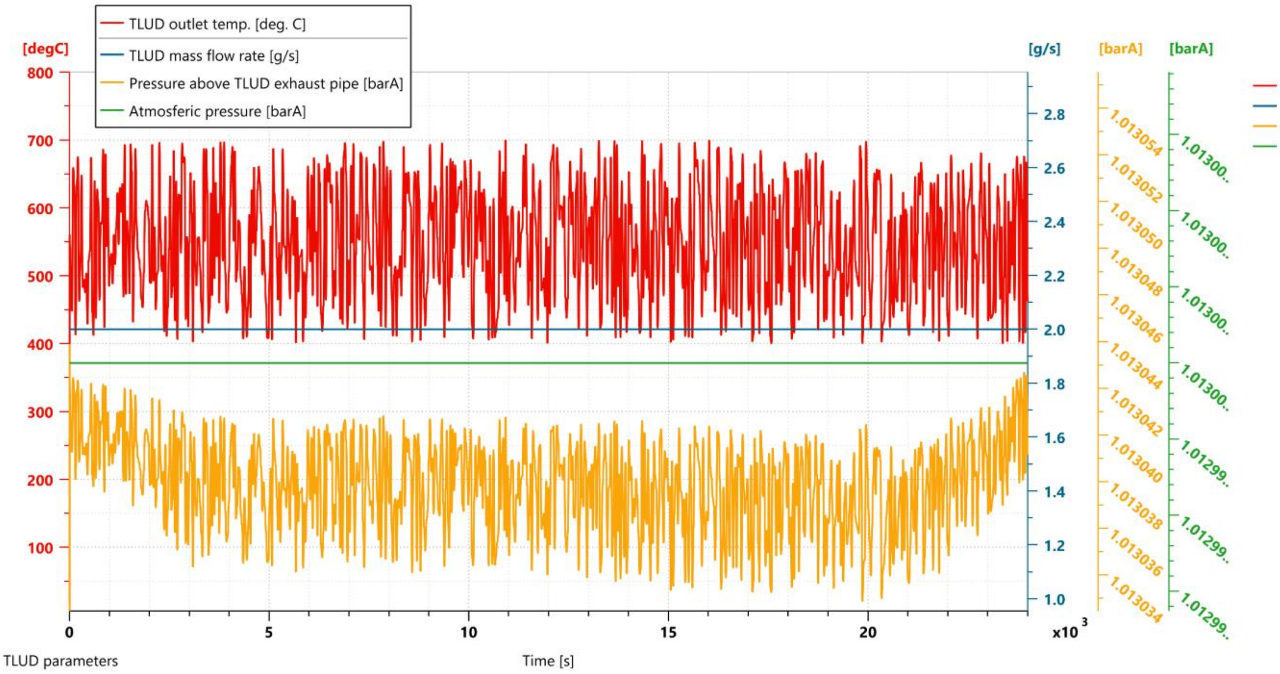


Fig. 7. Time variation of the parameters of the TLUD type gasifier (outlet temperature, hot air flowrate, outlet and atmospheric pressure)

Figure 8 shows the behavior of the butterfly valves, specifically the angles of the flaps, and how these adjustments regulate the flowrate of hot air to the drying chamber. This is crucial for understanding how the air flowrate regulation system maintains the desired temperature and airflow within the system.

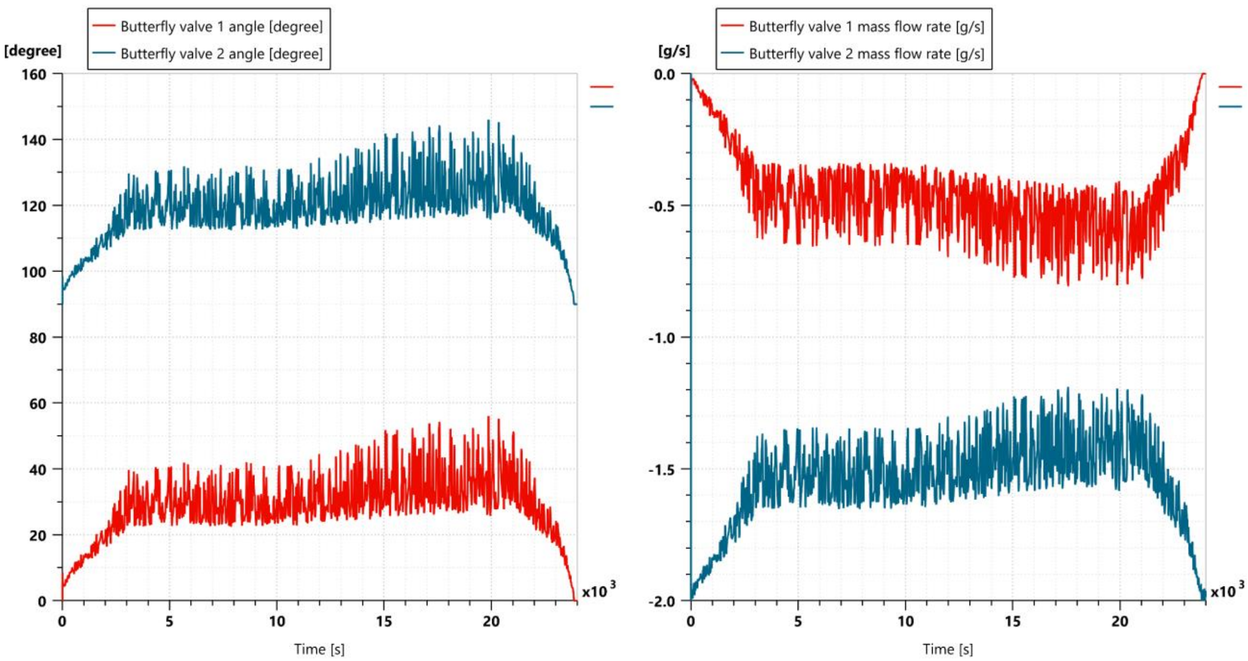


Fig. 8. Time variation of the angles of the flaps of the butterfly valves and of the flowrate of hot air regulated by them

Figure 9 displays the temporal changes in the drying chamber's temperature, the TLUD exhaust pipe temperature, and the pressures within the chamber and exhaust pipe. It provides insight into how well the system maintains the drying environment and the impact of gasifier output on the chamber conditions.

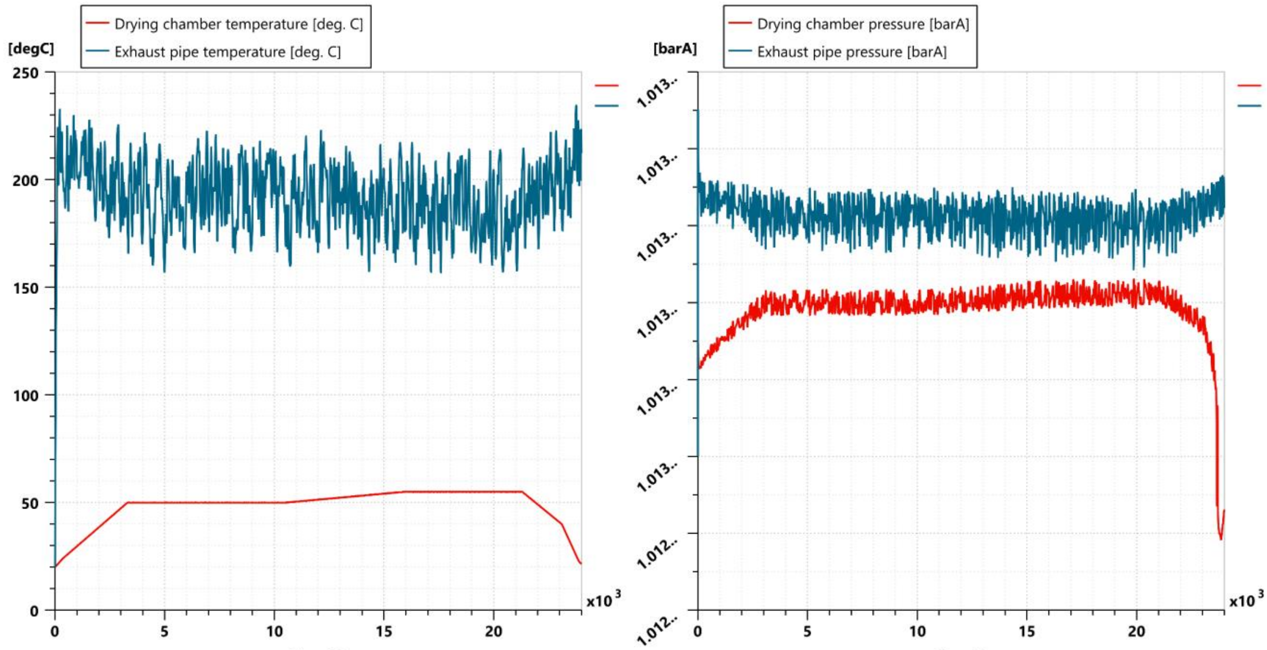


Fig. 9. Time variation of the temperature in the drying chamber, the temperature on the TLUD exhaust pipe and the pressure in the chamber and on the exhaust pipe

Figure 10 presents a detailed analysis of the temperature variations on the TLUD exhaust pipe, including instantaneous values, moving averages, and mean values. It highlights the stability and fluctuations of the temperature over time, which are critical for understanding the thermal dynamics of the drying system.

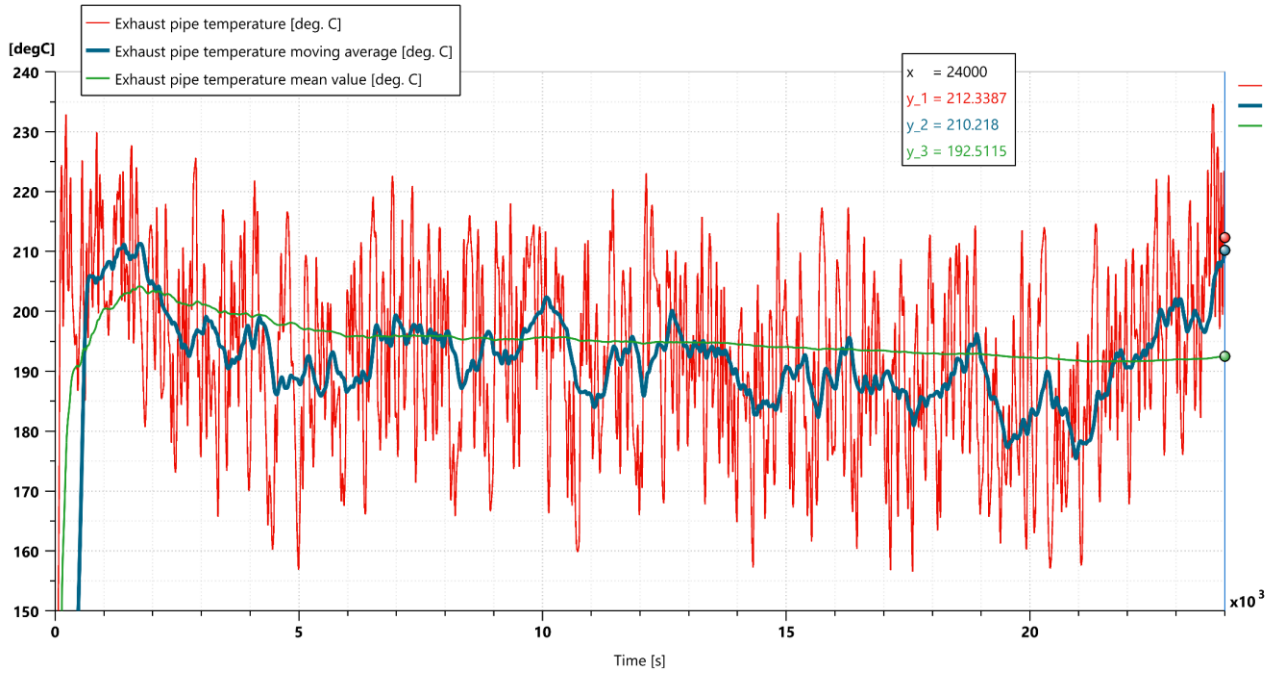


Fig. 10. Instantaneous variation over time of the temperature on the exhaust pipe of the TLUD, its moving average and its mean value

Figure 11 shows how the desired and actual temperatures in the drying chamber vary over time, along with the instantaneous temperature adjustment error (± 0.2 °C). It illustrates the effectiveness of the PID controller in achieving and maintaining the target temperature despite disturbances and fluctuations.

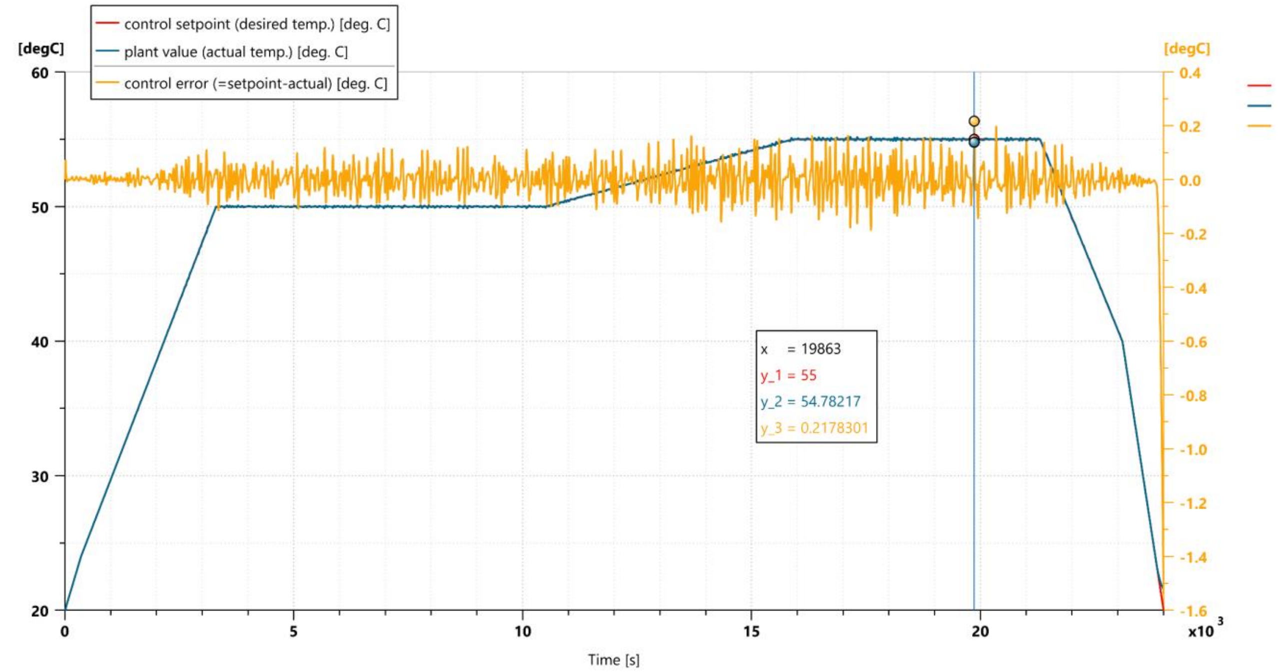


Fig. 11. Time variation of the automatic adjustment parameters (desired temperature, achieved temperature and instantaneous temperature adjustment error in the drying room)

Figure 12 shows the temperature-dependent changes in the angle of the butterfly valve disk and its frequency analysis (FFT). The FFT provides insight into the frequency components of the valve adjustments, which is useful for understanding the dynamic behavior and control actions within the system.

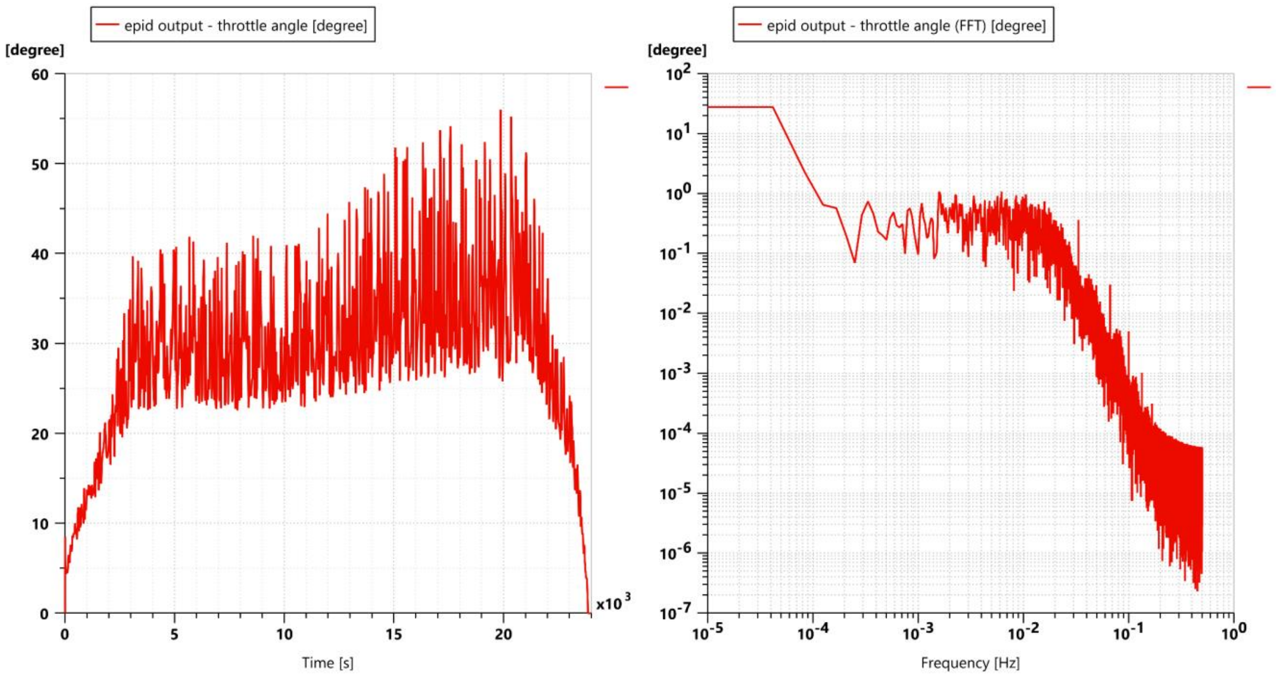


Fig. 12. Time variation of the angle of the butterfly valve disk and its FFT

Figure 13 compares the estimated mass of mulberry leaves during the drying process with experimentally obtained values, highlighting the instantaneous error and RMSE. It demonstrates the accuracy of the neural network model in predicting the mass changes over time.

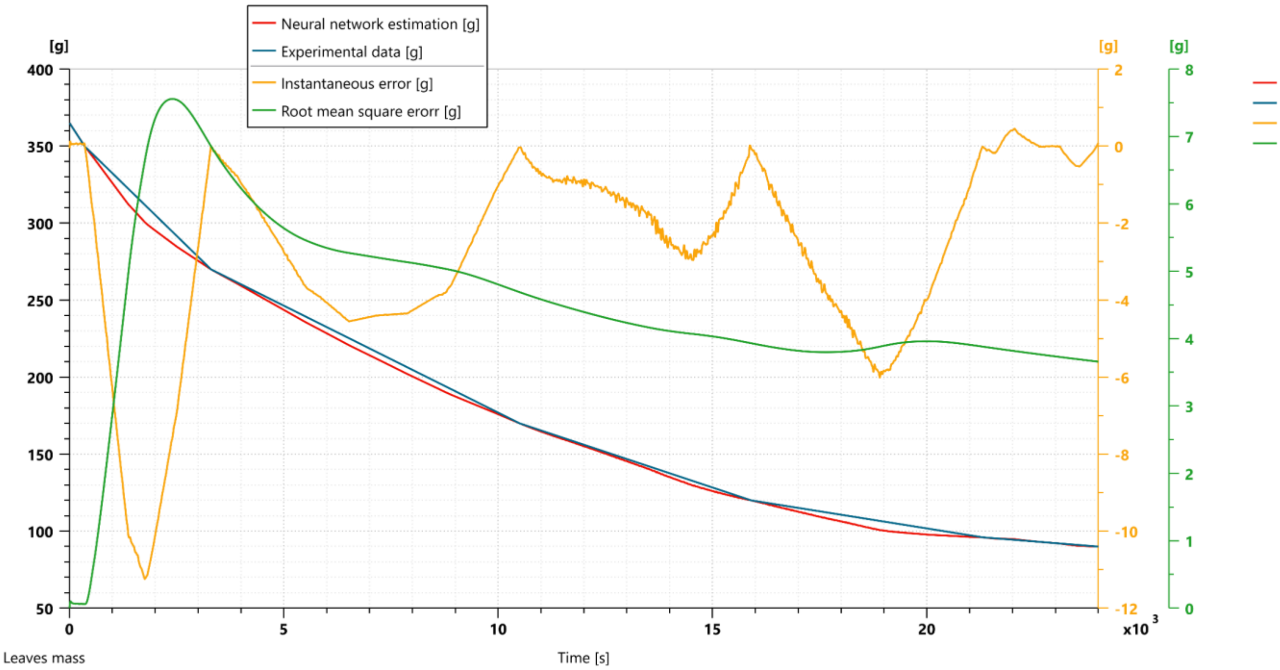


Fig. 13. Comparison of the time variation of the mass of mulberry leaves during drying, values estimated by the neural network, experimentally obtained values, instantaneous error and root mean square error

Similar to Figure 13, Figure 14 compares the estimated relative moisture with experimental values, showcasing the neural network's accuracy. The instantaneous error and RMSE provide a quantitative measure of the estimation performance.

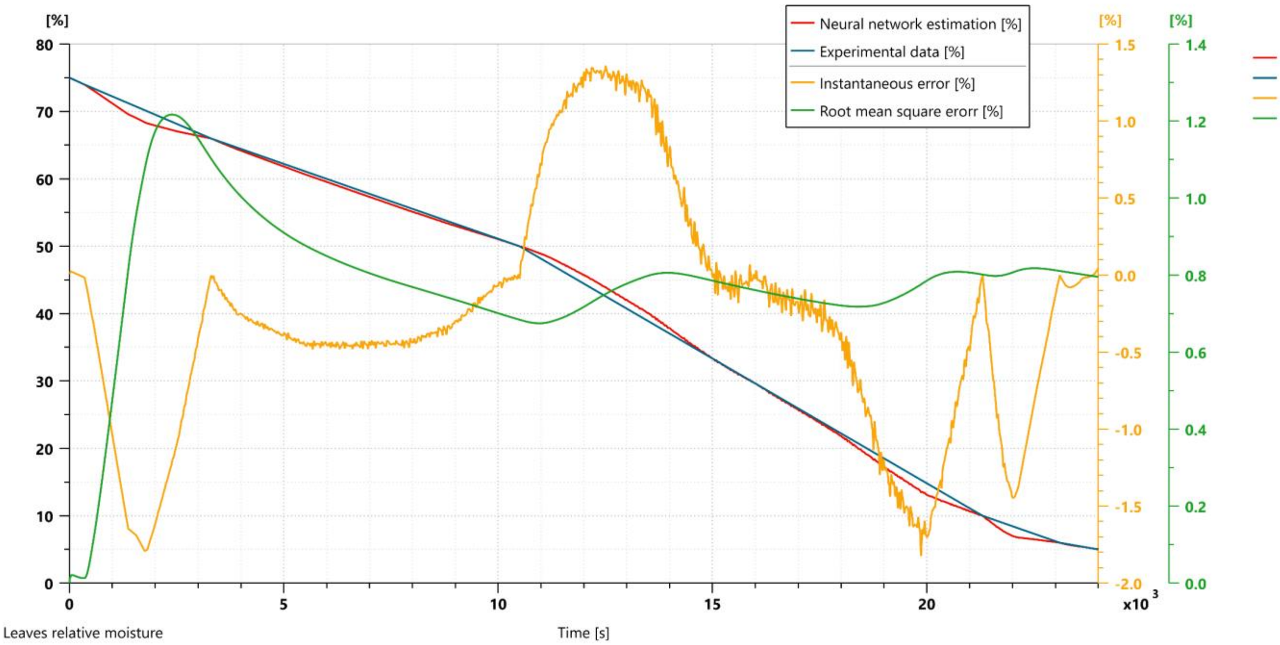


Fig. 14. Comparison of the time variation of the relative moisture of mulberry leaves during drying, values estimated by the neural network, values obtained experimentally, the instantaneous error and the root mean square error

Figure 15 illustrates the energy dynamics of the drying equipment, including total power, used power, lost power and overall efficiency. The moving average helps in smoothing out fluctuations and provides a clear picture of the system's energy performance over time.

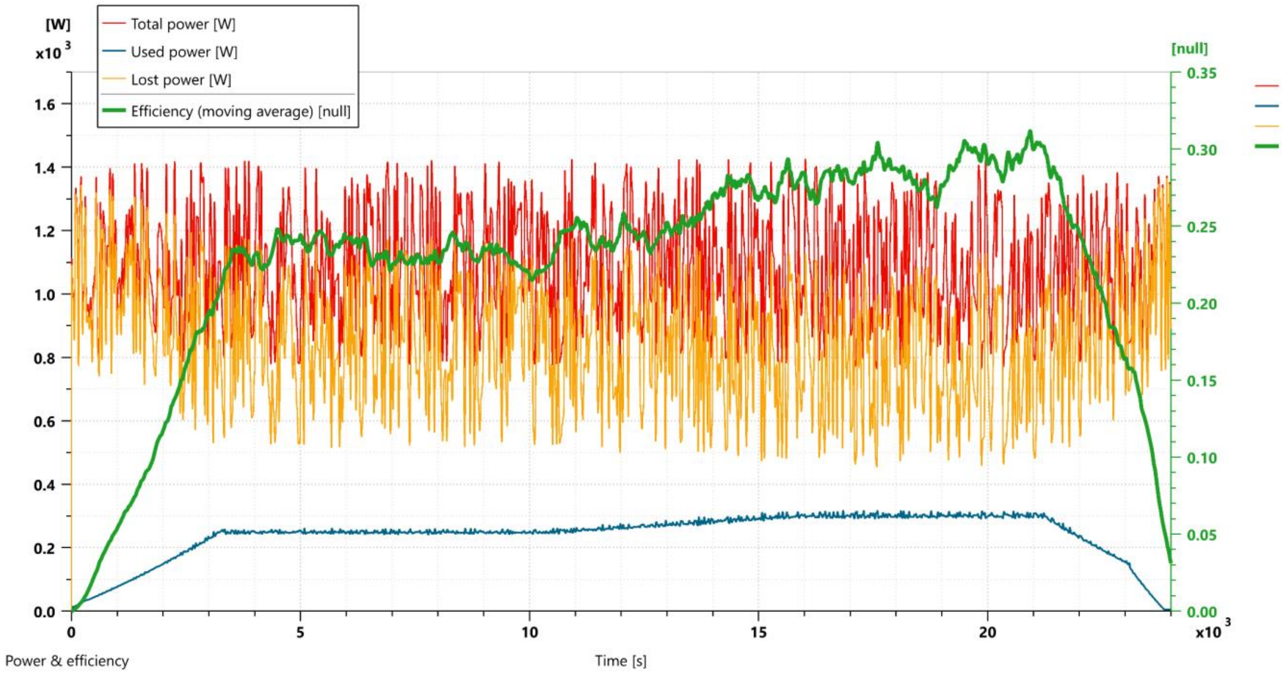


Fig. 15. Time variation of the total power, used power, lost power and efficiency of the drying equipment (moving average)

4. Conclusions

The research presented in this article has demonstrated the effectiveness and efficiency of a numerical simulation model for drying equipment tailored for vegetal matter, specifically integrating automatic process control and moisture estimation using a neural network. The study focused on developing and validating a comprehensive drying system using AMESim, incorporating key components such as a TLUD gasifier, an air flowrate regulation system, a PID controller with autotuning capabilities, and a neural network for moisture and mass estimation. The results offer significant insights into the dynamic interactions within the system and the potential for optimizing drying processes for agricultural applications.

One of the primary conclusions drawn from this study is the critical role of the PID controller with autotuning in maintaining the desired drying conditions within the chamber. The controller's ability to dynamically adjust the air flowrate in response to real-time temperature variations from the gasifier has been shown to significantly enhance the stability and consistency of the drying environment. The autotuning feature allows the PID controller to adapt its parameters automatically, ensuring optimal performance despite the inherent variability in the gasifier's temperature output. This adaptability is crucial for achieving the precise temperature control required for efficient and uniform drying of vegetal matter.

The integration of a neural network into the simulation model for estimating the relative moisture and mass of the drying leaves has proven to be highly effective. The neural network, trained with a substantial dataset, achieved exceptionally high training and validation fidelities of 99.99%. This high level of accuracy in moisture and mass estimation underscores the potential of machine learning techniques in enhancing the monitoring and control of drying processes. The use of six dense layers with ReLU activation functions and the stochastic gradient descent method for training contributed to the neural network's robustness and reliability. The successful implementation of this neural network demonstrates the feasibility of applying advanced data-driven approaches to optimize agricultural drying systems.

The dynamic behavior of the TLUD gasifier, characterized by its variable temperature output, necessitated the development of a sophisticated control mechanism. The study highlighted the effectiveness of the PID controller in compensating for these temperature fluctuations, thereby maintaining consistent drying conditions. Additionally, the butterfly valves' regulation of hot air flowrate was shown to be pivotal in achieving the desired temperature within the drying chamber. The comprehensive analysis of the gasifier's performance, including outlet temperature, hot air flowrate, and pressure changes over time, provided valuable insights into the operational dynamics of the drying system.

Furthermore, the comparison of estimated mass and relative moisture values with experimentally obtained data illustrated the neural network's accuracy and reliability. The low root mean square error (RMSE) in these comparisons validated the neural network's predictions, confirming its utility in real-time process monitoring and control. The study also demonstrated the neural network's ability to handle complex, non-linear relationships within the drying process, contributing to more precise and effective moisture management.

Future research will be able to explore several avenues building upon the findings of this study. Firstly, expanding the dataset used for training the neural network to include a wider variety of vegetal matter could enhance the generalizability and applicability of the model. This would involve collecting experimental data from different types of fruits or parts/organs with active principles intended for the valorization of medicinal plants, thereby broadening the scope of the drying system. Additionally, investigating the potential of other machine learning algorithms, such as convolutional neural networks or long short-term memory networks, could offer further improvements in prediction accuracy and system performance.

Another promising direction for future research is the integration of advanced sensor technologies to provide more granular and real-time data on the drying process. Implementing sensors that can measure additional parameters, such as air moisture, leaf surface temperature, and gas composition, would enrich the dataset and potentially lead to even more accurate neural network models. These enhancements could facilitate the development of a fully automated drying system capable of real-time adjustments based on comprehensive environmental data.

Therefore, it can be stated that this study has successfully developed and validated a numerical simulation model for a plant and fruit drying system, incorporating advanced control mechanisms and machine learning techniques. The integration of a PID controller with autotuning capabilities and a highly accurate neural network for moisture estimation has demonstrated the potential for significant improvements in drying process efficiency and product quality. The findings underscore the importance of dynamic control and data-driven approaches in optimizing agricultural drying systems. Future research should focus on expanding the model's applicability and integrating advanced sensor technologies to further enhance the precision and automation of drying processes.

Acknowledgments

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