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DIGITALISED NONWOVEN MANUFACTURING FOR REDUCED ENERGY CONSUMPTION AND EFFICIENT PRODUCTION RATES

AZALTILMIŞ ENERJİ TÜKETİMİ VE VERİMLİ ÜRETİM ORANLARI İÇİN DİJİTALLEŞEN NONWOVEN ÜRETİMİ

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DIGITALISED NONWOVEN MANUFACTURING FOR REDUCED ENERGY CONSUMPTION AND EFFICIENT PRODUCTION RATES

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ABSTRACT: The requirements placed on the textile industry are changing drastically. Zero-emission targets for 2030 and beyond require cross-sectoral changes. This also challenges the textile industry to find viable all-in solutions that satisfy social, economic, and sustainable requirements. Currently, the use of textiles in transdisciplinary sectors demands a high level of tailor-made solutions. This requires a broad understanding of the processed materials, complex multiphysics as well as machine settings. Hence, to consolidate high production rates with optimal energy consumption and the use of sustainable resources, systematic research and product development need to be pursued. The digitalisation of research and production in the textile industry aids to close the gap between the complex production processes and the quality measure of the end products. For this purpose, a systematic approach comprising experimental measurements and emerging digital technologies is used. nonwoven manufacturing machine park results have been used for the benchmark study.

Keyword: AI, Nonwoven, Multiphysics, Digitalisation, Digital twin, Machine-Learning

AZALTILMIŞ ENERJİ TÜKETİMİ VE VERİMLİ ÜRETİM ORANLARI İÇİN DİJİTALLEŞEN NONWOVEN ÜRETİMİ

ÖZ: Tekstil endüstrisine getirilen gereksinimler büyük ölçüde değişiyor. 2030 ve sonrası için sıfır emisyon hedefleri, sektörler arası değişiklikler gösteriyor. Bu aynı zamanda tekstil endüstrisini sosyal, ekonomik ve sürdürülebilir gereksinimleri karşılayan uygulanabilir hepsi bir arada çözümler bulmaya zorluyor. Şu anda, disiplinler arası sektörlerde tekstil kullanımı, yüksek düzeyde özel yapım çözümler gerektirmekte ve bu durum işlenmiş materyallerin, karmaşık multifiziğin yanı sıra makine ayarlarının geniş bir şekilde anlaşılmasına duylan ihtiyacı artırmaktadır. Bu nedenle, yüksek üretim oranlarını optimum enerji tüketimi ve sürdürülebilir kaynakların kullanımı ile birleştirmek için sistematik araştırma ve ürün geliştirmenin sürdürülmesi gerekmektedir. Tekstil endüstrisindeki araştırma ve üretimin dijitalleştirilmesi, karmaşık üretim süreçleri ile son ürünlerin kalite ölçüsü arasındaki boşluğun kapatılmasına yardımcı olur. Bu amaçla, deneysel ölçümleri ve gelişen dijital teknolojileri içeren sistematik bir yaklaşım kullanılmış, karşılaştırmalı çalışma için ise nonwoven (dokusuz yüzey) üretim hattı sonuçlarından (verilerinden) faydalanılmıştır.

Anahtar kelimeler: AI, Nonwoven, Çoklufizik, Dijitalleşme, Dijital ikiz, Makine-Öğrenmesi

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1. INTRODUCTION

The recognition of climate-neutral manufacturing and sustainable R&D has raised great attention in transdisciplinary deep-tech sectors such as advanced textile materials, energy or electrified vehicles for many years. Worldwide a strong commitment continues for reduced energy consumption [1]–[4] and to improve production efficiency. Consumers from various sectors are increasingly demanding tailor-made textile products, influencing the production rates by affecting the processes and product quality. The textile sector is also challenged to find satisfactory all-in solutions to forge sustainability and contribute to change.

This requires digitalisation-assisted production as well as systematic research and product development procedures. High production rates with optimal energy consumption and the use of sustainable resources demand extensive knowledge of the processes and product behaviour. The result depends decisively on the quality and quantity of the acquisition, processing and analysing of available data. In the textile industry, enough measurements are usually collected for quality control. However, key data available is usually lacking that links the main and interaction effects of the process parameters with the product quality. Moreover, an improved understanding of the processed materials, complex multiphysics, as well as machine settings, is required.

This means that information can not purely rely on experimental data-driven information transfer - especially in production plants where the optimisation of textile machinery, processes and fabrics for customer-specific cases is critical. The emerging hybrid artificial intelligence-multiphysics process will be demonstrated in this context. The study uses the optimisation of complex nonwoven production machines as an example to improve production rates and reduced energy consumption. The study aids to close the gap between systematic research and industrial challenges in production.

2. RESEARCH METHOD

To assess and optimise textile machinery, production processes as well as materials or product quality, traditional numerical methods such as the FEM or CFD are frequently used. Experimental data are used to validate and provide the input data for this kind of multiphysics analysis. Typically, sampling-based approaches, trial and error or techno-economic assessments are used in sensitivity studies to aid in improved understanding and to estimate operating efforts based on technical or financial input. However, in cross-sectoral industries such as the textile industry, the desired outcome is strongly tied to the integrated approach of R&D and production, as rapid response to changes is demanded. Thus, detailed modelling and simulation have been intensively used in this current study to improve the understanding and interpret the relationship between process parameters, machine components as well as product quality interactions.

The current study uses an experimentally validated digital twin model of the machine and AI-based machine learning for accelerated process optimisation as a design tool. Experimentally determined data from industry has been used as boundary conditions to mimic and calculate the thermo fluid flow of the complex textile machine architecture. Figure 1 displays the industrial nonwoven manufacturing machine from which experimental data was gathered for boundary conditions and validation purposes.

2.1. Digital Twin and Multiphysics Modelling of the Machine

The digital twin of the nonwoven machine has been constructed using computer-aided engineering tools. The machine system attributes including the textile transport belt, drying drum components as well as the nonwoven web are considered. To ensure a realistic portrayal of the industrial machine, each component has been characterised and considered in complicated CFD analyses. The experimental validation and detailed procedures including thermal and flow measurements have been elucidated in previous studies conducted on pilot scale machines such as those given in Ref. [5], and will not be detailed further.

2.2. Proof of Concept and Data Generation

The thermal fluid flow of the system has been numerically simulated using the nonwoven machine 's digital twin. To simulate the complicated behaviour, the permeabilities of the system attributes and thermophysical material properties have been incorporated. The rotation of the machine has been represented as a moving reference frame to also represent the machine's actual drum rotation. The model will be used to demonstrate and examine various thermofluid process conditions. Based on a D-optimal design of experiments (DoE) approach, a systematic investigation for data collecting is performed. For this purpose, the effects of three operating parameters on the textile machine have been assessed methodically. The parametric research will serve as an illustrative reference for decreasing the prediction time of conventional numerical approaches and enhancing the understanding required to develop optimum machine settings for desired process and product qualities. Moreover, it generates the data for the development and training of an AI-based machine learning model. Table 1 illustrates the used parameters.

CFD simulations were calculated to represent the various factor-level combinations that are utilised. As the fluid velocities and the associated temperatures determine the amount of energy introduced into the system, they are selected as variables. The nonwoven product quality is associated with the quality of fibre bonding during the manufacturing process. Therefore, it is also important to predict the temperature distribution of the nonwoven web to evaluate the quality of the product. The measure for this is set as the melting temperature of the used thermoplastic fibres. In this example, this has been set as technical nylon 66 with a melting point temperature of 221°C. This must be achieved in the most efficient way to obtain high production rates.

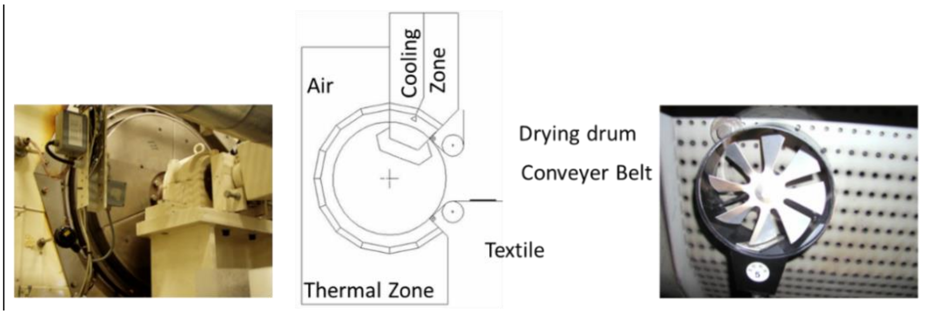

Figure 1. Industrial nonwoven machine details during the measurements taken from inside.

Table 1. Investigated variables used for the systematic assessment.

Factor level	-1	0	1
Air Temperature [°C]	225	230	235
Air velocity [m/s]	0.7	2	4
Dryer rotation speed [rad/s]	0.7	0.8	0.9

2.3. Machine Learning Model Development and Training

An analysis based on the machine's thermofluid flow behaviour and optimisation capacity has been explored as a consequence of the successful application of AI capabilities. The processed and stored data also helps the problem's scalability. By working with machine learning (ML) techniques based on artificial intelligence (AI), the execution of increasingly complicated transient CFD analyses is compensated. In this work, a link between factors and the nonwoven web temperature was found using supervised learning. As the researched variables and output are numerically predicted, a mathematical algorithm is used to understand the patterns contained in the data to produce new predictions. The learning-training procedure in machine learning involves the separation of input data into training data and test data. A supervised learning-training procedure requires data. The initial set of simulation data calculated numerically is used to shape the training data, which is used to train the model, while the test data are used to evaluate the model's accuracy. A cross-validation procedure is utilised to divide the data for training purposes. To enhance the reduction of energy consumption and control of the process, machine learning predictions will provide invaluable information. Thus, specified nonwoven temperatures of the manufacturing process can be generated, allowing it to be processed with the most efficient machine settings for reduced energy consumption. The flow chart of the overall optimisation procedure is depicted in Figure 2.

3. RESULTS

The experimental measurements performed on the used nonwoven machine revealed a non-uniform dispersion of fluid flow along the rotating machine width. The rotating speed of the machine is dependent on the conveyer belt speed; therefore, it has been essential to comprehend the rotational thermos fluid through the system components and the textile fabric over time. The results provided a data pool for the successful development of a machine learning model for optimisation purposes. Figure 3 displays an example of the transient temperature distribution results produced by the digital twin of the machine that was created to effectively replicate the thermo fluid flow within the machine. The results are taking into account the machine's rotation and the complex material behaviour of all system components.

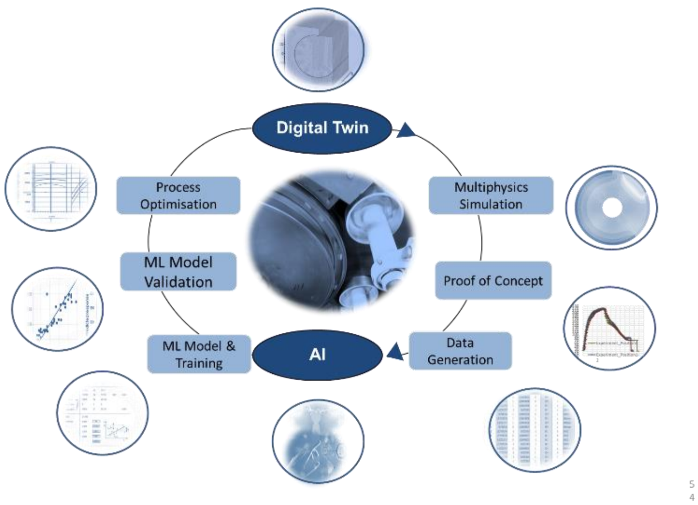

Figure 2. Flow chart of the textile machinery process optimisation using AI-based machine learning.

The nonwoven temperature has been selected for the optimisation criteria to achieve a controlled process with desired product quality. Nonlinear analysis of the data has been undertaken in order to grasp the mathematical relationship between the parameters throughout the machine learning model development phase. Figure 4 depicts the results for the main machine parameter effects on the nonwoven temperature.

The predicted outcomes provide the necessary data for statistically reliable AI analyses. Within a 99% confidence interval, a multi-regression analysis determined the relationship between the investigated variables and the mass-weighted nonwoven product temperature. The results of the analysis indicate that a significant portion of the data variance can be explained by the model. This is evident from the coefficient of determination value (R2) of 0.999 and root-mean-square (RMS) of 0.29. This directly enables us to identify the variable with the greatest potential for improvement. The air temperature indicates having the greatest impact among the demonstrated three variables. But the interesting information has been how these variables interact and affect the nonwoven temperature. Figure 5 demonstrates the relationship between these parameters and the nonwoven temperature.

The interactions of the investigated machine parameters have a considerable influence on the nonwoven web temperature. Nonlinear effects are observable considering the air velocity Fig. 5 (a) and the machine rotational speed Fig. 5 (b), whereas the effect of air temperature Fig. 5 (c) shows a linear effect on the nonwoven temperature response. The projections reveal a mid-range air velocity operation as favourable, whereas the lower end of the rotating speed demonstrates a better nonwoven temperature response. The predictions of the model are in excellent agreement with the observations of the machine-learning model, suggesting its use for optimising machine operation.

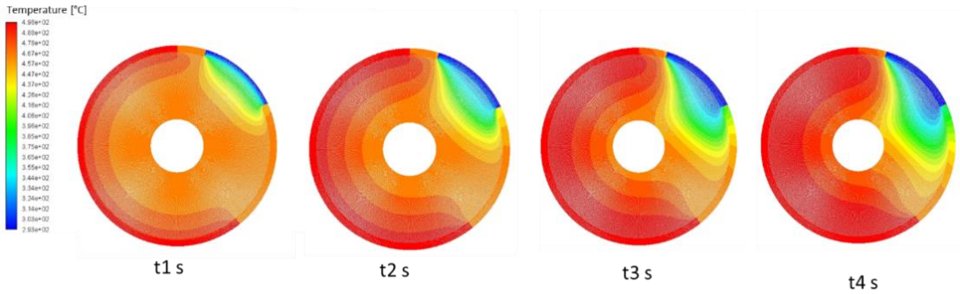

Figure 3. Temperature distribution inside the rotating machine and transported textile.

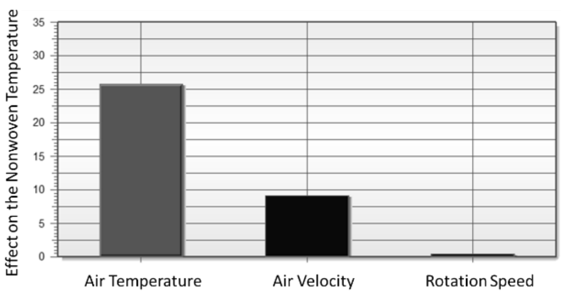

Figure 4. Main parameter effects on the nonwoven fabric temperature value.

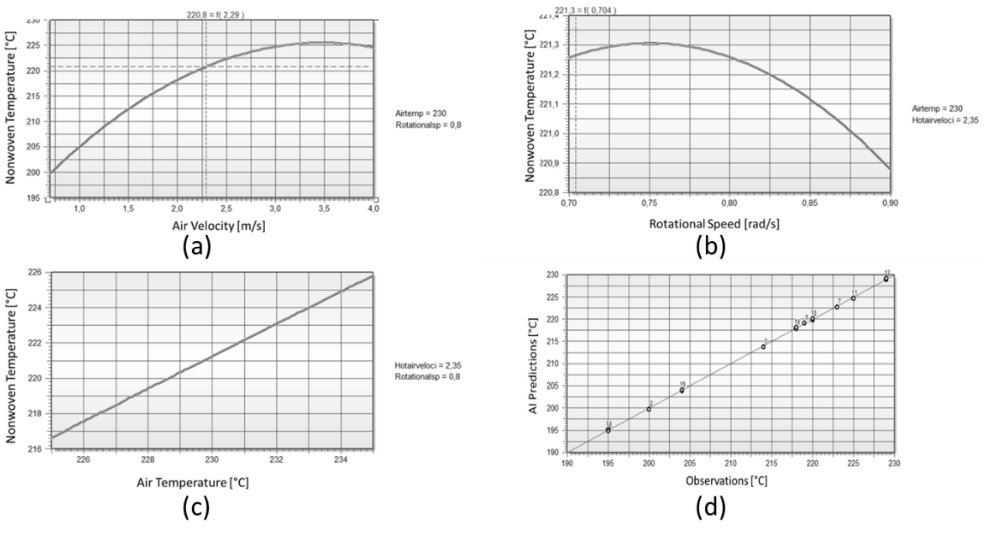

Figure 5: Interacting effects on the nonwoven fabric temperature value.

The trained machine learning model was used to estimate the ideal machine operation point for minimising energy consumption while maintaining the target level of product quality. This might be accomplished by locating the optimal temperature at which the nonwoven material hits 221°C. It should be noted that characteristics such as time of operation and additional aspects may be considered; however, for the purpose of the study and the generated training data, a machine process time of 20 seconds has been considered and its response has been investigated. Figure 6 summarises the results.

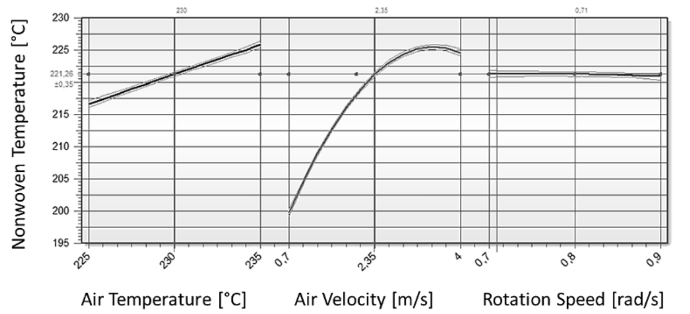

Figure 6: Interacting effects on the nonwoven fabric temperature value.

The optimisation procedure has been carried out for various distinct cases to predict the optimal machine operational points. The set parameter values are labelled in the upper portion of each graph, and the response output value is depicted horizontally along the axis displaying the nonwoven fabric temperature. Using the considered parameters and established levels, an optimal operation with the lowest energy usage while maintaining the specified fabric temperature of 221°C could be achieved. The air feed temperature set to 230°C and an air velocity of 2.35 m/s have shown to be energy efficient. Retaining a rotation speed of 0.7 rad/s has been sufficient for maintaining the target nonwoven temperature. Using the model, it was possible to forecast the operating behaviour of the manufacturing process by optimal adjustment of the chosen machine parameters, as demonstrated by the results.

4. CONCLUSION

The introduced study aims to demonstrate the use of emerging digital technologies in textile industry research and product development. An AI-based machine learning model was developed using a digital twin model of an industrial nonwoven manufacturing machine that has been experimentally validated. The model successfully determined the main and interaction effects of machine parameters such as air temperature, air velocity and rotational speed of the machine. The operational machine settings have been optimised with the aid of improving process and product quality. An air temperature of 230°C and an air velocity of 2.35m/s are shown to be maintaining the required nonwoven temperature of 221°C Thus, an optimal bonding temperature could be predicted with the most efficient machine settings for the selected parameters. The power of digital methods-based optimisation proved to be a very cost-effective way to assist sustainable industrial research and development. Moreover, the time and resource-efficient approach also mitigated hazards due to experimentation on thermal machinery.

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