PHYSICS-INFORMED HYBRID MACHINE LEARNING FOR RESIDUAL MOISTURE PREDICTION IN ROLLER PRESSING OF LEATHER SEMI-FINISHED MATERIALS

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K E Y W O R D S

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A B S T R A C T

Roller pressing of leather semi-finished materials is a complex multiparametric technological process in which mechanical deformation, contact pressure, liquid filtration, roller kinematics, and material moisture interact in a nonlinear manner. Conventional mathematical and automatic control approaches are often developed around a limited number of process parameters and therefore have difficulties in representing the combined influence of variable material properties and operating conditions. At the same time, machine learning (ML) methods can identify nonlinear dependencies from experimental data but do not inherently preserve the physical constraints of the technological process. This study proposes a Physics-Informed Hybrid Machine Learning (PI-HML) approach for residual moisture prediction in leather roller pressing. The proposed framework integrates a physical model of contact deformation and moisture filtration with a data-driven ML model through a unified Physics-Informed Information Model (PIIM). The methodological framework was derived from the physical and technological relationships of a two-roll pressing system and implemented for a pilot computational evaluation using 21 experimental observations with roller load intensity, roller radius, roller speed, and residual moisture as the principal variables. Leave-One-Out Cross-Validation was applied to compare Linear Regression, Support Vector Regression, Random Forest, Gradient Boosting, and XGBoost models. In the pilot experiment, XGBoost achieved the best data-driven performance with an MAE of 1.355% and RMSE of 2.136%, while the proposed physics-informed fusion reduced these errors to 1.289% and 1.969%, respectively, with $R^2 = 0.791$. These results demonstrate the feasibility of integrating physical process knowledge with ML for more consistent technological prediction. The proposed framework provides a methodological basis for the subsequent development of sensor-driven adaptive intelligent control of roller pressing machines.

1. Introduction

Leather manufacturing is characterized by a sequence of interconnected technological operations in which the state of the semi-finished material formed at one stage directly influences the quality and efficiency of subsequent operations. Moisture regulation and thickness stabilization are particularly important because they determine the readiness of the semi-finished material for further mechanical and finishing operations. Roller pressing plays a key role in this context because excess moisture is removed from the material under mechanical compression, while the thickness and physical state of the material are simultaneously modified [1,4,5,8,9].

A roller pressing machine should therefore not be considered only as a mechanical device. From a systems perspective, it is a multiparametric and dynamic technological system in which input variables, control actions, internal physical states, and output variables are strongly interconnected. The principal technological variables include contact pressure, hydraulic pressure, roller speed, material feeding speed, initial moisture, material

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thickness, elastic characteristics, and friction conditions. The outputs include residual moisture, final thickness, energy consumption, productivity, and product quality indicators. The relationships between these variables are generally nonlinear [1-3,11].

The technological complexity increases because the processed leather material exhibits elastic, viscoelastic, and partially plastic deformation. At the same time, the compression of the porous material induces liquid displacement and filtration. Therefore, mechanical deformation and moisture transport cannot be considered as completely independent processes. Excessively low pressure can result in insufficient moisture removal, whereas excessive pressure may negatively affect the internal fibrous structure of the material [2,4,5,7-9,13].

Modern industrial digitalization has created new opportunities for technological monitoring. Pressure, temperature, moisture, roller speed, hydraulic parameters, and energy consumption can be continuously measured using sensors. However, sensor data are characterized by high dimensionality, temporal variability, measurement noise, and complex relationships between process variables. As a result, sensor information cannot always be transformed directly into an effective control decision without appropriate preprocessing, identification, prediction, and decision-support mechanisms [3,4,11,12].

Machine learning provides a promising solution to this problem because ML algorithms can identify complex nonlinear relationships and estimate future technological states from historical observations. Nevertheless, a purely data-driven model has an important limitation: it does not automatically know whether its predictions are physically plausible. This problem becomes especially important when the available training dataset is small or does not cover all possible operating modes. The first research file explicitly identifies the insufficient use of real-time technological identification, ML-based prediction, and automated decision formation in roller pressing as a research gap [3,11,14].

From the point of view of process analysis and management, the central scientific problem is not simply to predict a technological parameter. It is to transform a physical technological process into a single information and control system in which physical laws, measured or reconstructed data, predictive models, and management decisions systematically interact. The proposed methodological concept follows the following structure:

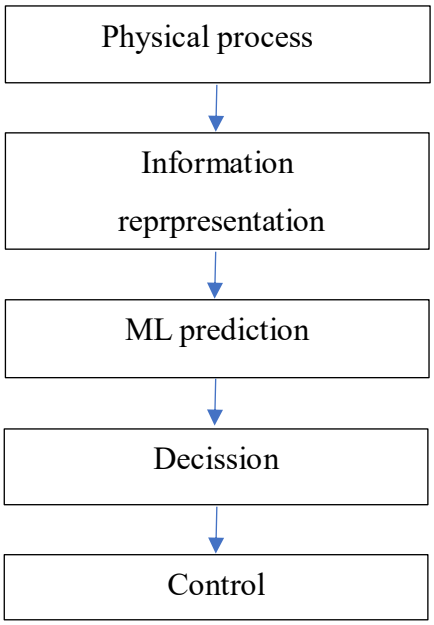


Fig. 1. Structure of a unified information and management system for the process

The above information is dedicated of develops precisely this transition from a physical description toward an information-oriented dynamic representation. It defines the process in terms of control variables, internal physical states, observable outputs, contact pressure, hydraulic pressure, deformation, filtration, and residual moisture.

A two-roll system is adopted as the physical basis. In this model, the roller geometry, working gap, pressing load, material thickness, roller velocity, and moisture state determine the deformation and filtration behavior. The physical description is further generalized into a state-space representation in which control variables, state variables, disturbances, and observable outputs are distinguished.

The objective of this study is therefore to develop and computationally evaluate a Physics-Informed Hybrid Machine Learning framework for predicting residual moisture in leather roller pressing, using the physical relationships of the roller pressing process together with experimental

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observations. The specific objectives are: (i) to formulate a unified physical-information representation, (ii) to establish a machine-learning prediction framework, (iii) to integrate the physical and data-driven components into a PI-HML architecture and (iv) to compare the proposed approach with conventional data-driven ML models.

The principal contribution of the study is not the replacement of the physical model by machine learning. Instead, the contribution is the integration of physical process knowledge and data-driven prediction within a unified information model. This distinction is important because the proposed approach is intended to form the basis for subsequent intelligent monitoring and adaptive control.

2. Materials and Methods

2.1. Physical representation of the roller pressing process

The physical model is based on a two-roll pressing module in which the material passes through a compression zone between rotating rollers. The roller radii, working gap, initial material thickness, compressed thickness, pressing load, and roller kinematics form the basic geometric and technological parameters.

The relative compression deformation of the material can be written as:

$$\varepsilon = \frac{H - h}{H},$$

where H is the initial thickness of the semi-finished leather material and h is the thickness after compression.

The roller kinematics are represented by the relationship between angular velocity and linear roller velocity:

$$V_i = \omega_i R_i,$$

where V_i is the linear velocity of the i-th roller, ω_i is its angular velocity, and R_i is its radius.

The pressing process is characterized by a load intensity Q. Within the physical model, the mechanical interaction is represented by normal and tangential forces, support reactions, and torque. This interpretation follows the contact-mechanical formulation of the two-roll module.

The material is considered as a two-phase medium containing a solid fibrous structure and liquid moisture. Therefore, residual moisture is treated as one of the principal technological outputs.

A key physical assumption is that the total pressure in the compression zone consists of mechanical and hydraulic components:

$$p = p_m + p_h,$$

where p_m represents the mechanical compression component and p_h represents hydraulic pressure associated with liquid movement inside the porous material.

The moisture transport is associated with the pressure gradient and filtration properties of the material. In generalized form, Darcy-type filtration can be represented as:

$$q = -K\nabla p_h,$$

where q is the liquid filtration flux vector and K is the effective filtration coefficient.

The second file explicitly introduces this relationship as a physical basis for representing moisture removal from the compressed material. The moisture balance can then be represented conceptually as:

$$\frac{dW}{dt} = -\frac{\dot{m}_{out}}{m_d},$$

where W is the moisture state, $\dot{m}_{out}$ is the rate of moisture removal, and m_d is the dry-material mass.

Residual moisture is determined by the balance between initial moisture and removed moisture:

$$W_{res} = W_0 - W_{out}.$$

2.2. Unified information representation

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From a systems perspective, the roller pressing process can be described using three interconnected groups of variables:

$$u(t) = \begin{bmatrix} Q(t) \\ V(t) \\ \delta(t) \end{bmatrix},$$

$$x(t) = \begin{bmatrix} h(t) \\ \varepsilon(t) \\ W(t) \\ p(t) \\ p_h(t) \\ \sigma_n(t) \end{bmatrix},$$

and

$$y(t) = \begin{bmatrix} W_{res}(t) \\ h(t) \\ p(t) \end{bmatrix}.$$

Here, u(t) represents control variables, x(t) represents internal physical states, and y(t) represents observable process outputs.

A general state-space representation is:

$$x_{k+1} = F(x_k, u_k, d_k),$$
$$y_k = G(x_k, u_k),$$

where d_k represents disturbances and model uncertainties.

The main idea of this work is to explicitly verify this state-space representation as a basis for intelligent coupling of physical process control and evaluation. For future sensor integration, the observable sensor vector can be represented as:

$$s_k = [Q_k, \ p_k, \ V_k, \ h_k, \ W_k, \ T_k, \ a_k, \ U_k, \ I_k]^T. \qquad (1)$$

At the present stage, however, actual time-series sensor observations are not available. Therefore, Eq. (1) is treated as the target information structure of the future sensor layer rather than as an experimentally measured dataset.

This distinction is important for methodological validity. The present quantitative analysis uses tabulated process observations, whereas the sensor-oriented model defines how future real-time measurements can be integrated into the same computational framework.

2.3. Experimental reference dataset

For computational validation, the experimental observations reported in [1,2] study were used as the reference dataset. The dataset consists of 21 experimental combinations involving load intensity Q, roller radius R, roller speed V, and measured residual moisture W_{ost}.

The principal parameter ranges are:

$$15 \le Q \le 65 \ kN/m,$$
$$0.058 \le R \le 0.170 \ m,$$
$$0.10 \le V \le 0.34 \ m/s.$$

The experimental table contains the residual moisture corresponding to each combination of these three factors.

The ML dataset can therefore be represented as:

$$\mathcal{D} = \{(Q_k, R_k, V_k, W_k)\}_{k=1}^{21}.$$

The input matrix and target vector are:

$$X = \begin{bmatrix} Q_1 & R_1 & V_1 \\ Q_2 & R_2 & V_2 \\ \vdots & \vdots & \vdots \\ Q_{21} & R_{21} & V_{21} \end{bmatrix}, \ y = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_{21} \end{bmatrix}.$$

An important statistical feature of the dataset is that the experimental variances were previously checked for homogeneity using Fisher's criterion. At a confidence level of $\alpha = 0.95$, the reported calculated Fisher statistic was below the corresponding tabulated value, supporting the statistical consistency of the experimental observations.

2.4. Machine-learning prediction models

Residual moisture prediction is formulated as a nonlinear regression problem:

$$\widehat{W}_{ost} = f_\Theta(Q, R, V),$$

where f_Θ is the regression function defined by a model with parameters Θ.

Five data-driven models were evaluated:

1. Linear Regression;
2. Support Vector Regression (SVR);

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3. Random Forest Regression;
4. Gradient Boosting Regression;
5. XGBoost Regression.

These models were selected to represent linear, kernel-based, bagging, boosting, and gradient-boosted tree approaches.

Because the available dataset contains only 21 observations, standard random train/test splitting may produce unstable conclusions. Therefore, Leave-One-Out Cross-Validation (LOOCV) was adopted:

$$\mathcal{D} = \mathcal{D}_{train}^{(k)} \cup \mathcal{D}_{test}^{(k)},$$

with:

$$| \mathcal{D}_{test}^{(k)} | = 1.$$

Every observation is thus used once as an independent validation point. The three principal evaluation metrics are Mean Absolute Error:

$$MAE = \frac{1}{N}\sum_{k=1}^{N} |W_k - \widehat{W}_k| .$$

Root Mean Squared Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \left(W_k - \widehat{W}_k\right)^2},$$

and coefficient of determination:

$$R^2 = 1 - \frac{\sum_{k=1}^{N} (W_k - \widehat{W}_k)^2}{\sum_{k=1}^{N} (W_k - \bar{W})^2}.$$

Lower MAE and RMSE indicate more accurate prediction, whereas higher R^2indicates that a larger proportion of the target variability is explained by the model.

2.5. Proposed Physics-Informed Hybrid Machine Learning model

The main methodological contribution of this study is the integration of physical and data-driven representations. The physical branch produces:

$$\widehat{W}_{phys} = F_{phys}(Q, R, V, \phi),$$

where ϕ denotes physical process characteristics.

The data-driven branch produces:

$$\widehat{W}_{ML} = F_{ML}(X),$$

where X contains the selected input variables.

The simplest hybrid formulation is a weighted fusion:

$$\widehat{W}_{PI-HML} = \alpha \widehat{W}_{phys} + (1 - \alpha)\widehat{W}_{ML},$$

where $\alpha \in [0, 1]$ represents the relative contribution of the physical and data-driven branches.

However, a fixed αdoes not fully exploit the idea of physical consistency. A more general formulation is:

$$\alpha_k = g\left(E_{phys,k}\right),$$

where $E_{phys,k}$ is a physical-consistency error and $g(\cdot)$ is an adaptive weighting function.

For the pilot computational study, the physical branch was represented by a quadratic response-surface approximation of the process relationships, while the data-driven branch was represented by XGBoost. Importantly, both branches were fitted independently within each LOOCV training fold in order to reduce information leakage.

The physics-informed information vector can be generalized as:

$$X_{PI} = \left[X_{data}, \phi_{phys}, r_{phys}\right]^T,$$

where: X_{data} contains experimental process variables, ϕ_{phys} contains physically derived features, r_{phys} contains discrepancies between the physical representation and observed behavior.

2.6. Proposed computational workflow

The complete computational procedure is defined as follows.

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Step 1. Load the experimental reference dataset:

$$\mathcal{D} = \{(Q, R, V, W_{ost})\}.$$

Step 2. Separate input variables and target variable.

Step 3. Normalize variables when required by the selected model.

Step 4. Perform LOOCV partitioning.

Step 5. Train the selected ML model on the training fold.

Step 6. Construct the physical approximation on the same training fold.

Step 7. Predict W_{ML} and W_{phys} for the left-out observation.

Step 8. Combine the two predictions:

$$\widehat{W}_{PI-HML} = \alpha \widehat{W}_{phys} + (1 - \alpha)\widehat{W}_{ML}.$$

Step 9. Calculate MAE, RMSE and R^2.

Step 10. Repeat the procedure for all 21 observations.

3. Results

3.1. Analysis of the reference experimental data

The 21 experimental observations cover a wide range of operating conditions. The measured residual moisture values vary from approximately 41.14% to 60.48%, demonstrating a substantial dependence of the process outcome on the selected operating parameters.

A preliminary monotonic analysis indicates that load intensity Q is the strongest individual factor associated with residual moisture reduction. The nonparametric Spearman correlation between Q and W_{ost} calculated from the reference dataset is approximately:

$$\rho_Q = -0.748.$$

For the roller radius and speed, the corresponding values are:

$$\rho_R = 0.378,$$
$$\rho_V = 0.450.$$

These values agree qualitatively with the technological interpretation provided by the reference research: increasing pressing load tends to increase moisture removal, whereas increasing roller radius and roller speed are associated with higher residual moisture under the studied conditions.

The reference study also reports the dependence of residual moisture on the process factors graphically, including the influence of roller speed and radius. The direction of these relationships provides an important physical consistency criterion for ML models.

3.2. Comparison of data-driven ML models

The following results were obtained from the 21-observation dataset using LOOCV and fixed computational settings for reproducibility.

Table 1.

Performance of data-driven models

Model	MAE (%)	RMSE (%)	R^2
Linear Regression	1.818	2.532	0.655
SVR	1.667	2.572	0.644
Random Forest	1.850	2.766	0.588
Gradient Boosting	1.417	2.120	0.758
XGBoost	1.355	2.136	0.755

The results show a clear difference between linear and nonlinear approaches. Linear Regression produced MAE = 1.818%, confirming that the three process variables explain a considerable but incomplete part of the moisture variability.

SVR reduced the MAE to 1.667%, indicating that nonlinear mapping can improve absolute prediction accuracy. However, the R^2 value remained relatively modest for the small dataset.

Random Forest produced the weakest overall data-driven performance, with MAE =

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1.850%and $R^2 = 0.588$. This result indicates that the bagging approach did not adequately generalize from the limited number of observations.

Gradient Boosting showed considerably stronger performance, with MAE = 1.417%, RMSE = 2.120%, and $R^2 = 0.758$.

XGBoost achieved the lowest MAE among the tested data-driven models:

$$MAE_{XGB} = 1.355\%.$$

Its R^2value of 0.755was close to that of Gradient Boosting. Therefore, XGBoost was selected as the principal data-driven component for the pilot PI-HML implementation.

3.3. Feature contribution analysis

An additional analysis of the XGBoost model trained on the complete reference dataset produced the following approximate feature importance values:

$$I_Q = 0.565,$$
$$I_V = 0.304,$$
$$I_R = 0.132.$$

Thus, load intensity Q had the highest contribution, followed by roller speed Vand radius R. This result is consistent with the experimental trends reported in the reference work, where load intensity plays a dominant role in residual moisture reduction. The reference experimental study also identifies Q, R, and V as the principal factors used to investigate residual moisture.

The importance ranking should not be interpreted as a causal physical law. Rather, it describes the predictive contribution of each variable within the chosen ML model and dataset. The physical interpretation is instead obtained by comparing the ML result with the known process relationships.

3.4. Physics-informed hybrid prediction

The reference research provides model-estimated residual moisture values $\widehat{W}_{ost}$ for the same 21 experimental observations. When these physical-model values are compared directly with the measured values, the resulting in-sample metrics are approximately:

$$MAE_{phys} = 0.671\%,$$
$$RMSE_{phys} = 0.857\%,$$
$$R^2_{phys} = 0.960.$$

These values demonstrate that the reference response-surface model describes the existing experimental points very closely. However, because the model values originate from a model fitted to the same experimental set, they represent in-sample agreement, not independent generalization performance.

To evaluate the PI-HML concept without using the left-out observation, a fold-wise physical branch and a fold-wise XGBoost branch were trained independently. A balanced fusion was then applied:

$$\widehat{W}_{PI-HML} = 0.5\widehat{W}_{phys} + 0.5\widehat{W}_{XGB}.$$

The resulting LOOCV performance was:

Table 2.

Pilot comparison of XGBoost and PI-HML

Model	**MAE (%)**	**RMSE (%)**	R^2
XGBoost	1.355	2.136	0.755
PI-HML	1.289	1.969	0.791

The proposed PI-HML therefore reduced MAE by approximately:

$$\Delta MAE = \frac{1.355 - 1.289}{1.355} \times 100 \approx 4.86\%. \quad (2)$$

The RMSE reduction was:

$$\Delta RMSE = \frac{2.136 - 1.969}{2.136} \times 100 \approx 7.79\% \quad (3)$$

The coefficient of determination increased from approximately 0.755 for XGBoost to 0.791 for PI-HML.

These results indicate that incorporating a physical branch improves the predictive behavior of the data-driven model under the present pilot conditions. The improvement should not, however,

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be interpreted as proof that the proposed PI-HML is universally superior. The dataset is too small for such a conclusion, and the physical branch itself depends on a simplified representation.

4. Discussion

The experimental analysis demonstrates three important findings.

First, the roller pressing process cannot be fully represented by a simple linear relation between the input variables and residual moisture. The performance of Linear Regression was clearly lower than that of Gradient Boosting and XGBoost. This observation is consistent with the physical analysis, which identifies deformation, contact pressure, filtration, and moisture transport as interacting nonlinear phenomena.

Second, the best-performing data-driven algorithms were tree-based boosting models. XGBoost provided the smallest MAE among the evaluated purely data-driven models, while Gradient Boosting yielded a very similar level of performance. This is reasonable because the available process variables interact nonlinearly and the experimental design is sparse.

Third, the addition of physical information improved the LOOCV performance of the XGBoost model. This is the central finding of the proposed approach. The physical model does not replace the ML model. Instead, it provides a structured representation of the known process behavior and acts as an additional source of information.

This concept is consistent with the physical model developed in the second file. There, the roller pressing process is described as a sequence linking mechanical deformation, contact pressure, hydraulic pressure, filtration, and residual moisture. The PI-HML formulation transfers this causal structure into the information-processing layer.

The distinction between prediction accuracy and physical consistency is particularly important. A purely data-driven model may obtain a low error in the region covered by training data while producing physically implausible predictions outside that region. In contrast, a Physics-Informed approach can incorporate the known structure of the technological process.

Thus, the scientific novelty of the present work is primarily methodological and algorithmic. The physical model is transformed into a structured information representation, the information representation is linked to ML, and the combined model is positioned as the predictive layer of a future adaptive control system.

5. Conclusion

This study presented a Physics-Informed Hybrid Machine Learning framework for residual moisture prediction in leather roller pressing. The proposed approach was developed from a physical representation of the two-roll pressing process, in which mechanical deformation, contact pressure, hydraulic pressure, moisture filtration, and residual moisture are treated as interconnected components of a single technological system.

A unified Physics-Informed Information Model was formulated to connect physical process variables with data-driven information. The resulting PI-HML framework combines a physical prediction branch with an ML branch, thereby preserving process knowledge while exploiting the nonlinear predictive capability of machine learning.

References

1. Turgunov, K.K. *Investigation of Contact Interaction in Roller Pairs of Leather Machines for Improving Product Quality and Production Efficiency*. PhD dissertation, Tashkent Architectural and Construction University, Tashkent, 2023. The dissertation develops the physical and experimental basis for two-roll pressing of leather semi-finished materials.
2. Hudayberdiyev M.Kh., Tojiboyev B.M., Ravshanov A.A. *Classification Of Earth Remote Sensing Images Using Artificial Neural Networks And Algorithms for calculation of estimates* // Bulletin of TUIT: Management and Communication Technologies № 2024 3(29).
3. Khudayberdiyev M.Kh., Tojiboyev B.M., Achilov B,S., Alimkulov N.M., Ravshanov A.A. *Integrating fractal dimension and time*

series analysis for optimized hyperspectral image classification // Advanced Computing: An International Journal (ACIJ), Vol.16, No.4, July 2025. Pp. 1-20

4. Kamilov Mirzoyan, Hudayberdiev Mirzaakbar, Khamroev Alisher. *The Procedure for Defining the best Recognition Module of the Algorithms for Calculating Estimates* // Techno-Societal 2018. Proceedings of the 2nd International Conference on Advanced Technologies for Societal Applications. Springer, Cham. - Pp 25-32.
5. Khurramov, Sh.R. *Some Questions of the Contact Interaction Theory in Two-Roll Modules*. Journal of Physics: Conference Series, 1546 (2020), 012132.
6. Khurramov, Sh.R. *Simulation of the Form of Contact Curves Rolls in Two-Roll Modules*. IOP Conference Series: Earth and Environmental Science, 614 (2020), 012096.
7. Khurramov, Sh.R., Khalturaev, F.S., Kurbanova, F.Z. *Deformation and Filtration Characteristics of a Leather Semi-Finished Product*. Studies in Systems, Decision and Control, Vol. 342, Springer, 2021.
8. Amanov, A., Khurramov, S.R., Bahadirov, G.A., Abdukarimov, A., Amanov, T.Y. *Modeling of Strain and Filtration Properties of a Semi-Finished Leather Product*. Journal of Leather Science and Engineering, 3(1), 14, 2021.
9. Бахадиров Г.А. *Выбор кривой поверхности при подаче листового материала в зону обработки.* // Динамика систем, механизмов и машин. –2016. – С.72-77.
10. Лапин И.Р. *Покрытия для валов прессовой части бумагоделательной машины*. // Новые импульсы развития: вопросы научных исследований. Серия «Механика и машиностроения» – 2020.– С. 94-96.
11. Khurramov Sh. R. *Filtration rates in roller pressing of fibrous materials" AIP Conference Proceedings*, MIP Injenering - III, Krosnoyarsk, Russia, 125 2402(2021)030042 https://doi.org/10.1063/5.0071266 .
12. Khurramov Sh. R, Khalturaev F.S., Buriev E.S. *Residual moisture concent in semi-finished leather under roller pressing. AIP Conference Proceedings*, MIP Injenering - III, Krosnoyarsk, Russia, 2402(2021)030038 https://doi.org/10.1063/5.0071265.
13. N. R. Yusupbekov, S. M. Gulyamov and M. Y. Doshchanova, "*Neural identification of a dynamic model of a technological process,*" 2019 International Conference on Information Science and Communications Technologies (ICISCT), Tashkent, Uzbekistan, 2019, pp. 1-5, doi: 10.1109/ICISCT47635.2019.9011912. (*bu adabiyotlar ro'yxatiga kirsin!*)
14. Хуррамов Ш.Р. *Теоретические основы контактного в взаимодействия в двухвалковых модулях и ее использование совершенствовании процессов механической обработки*. Дис. … докт. техн. наук. Ташкент: ТТИЛП, 2022. – 192 с.

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