PLOVDIV UNIVERSITY "PAISII HILENDARSKI"
FACULTY OF MATHEMATICS AND INFORMATICS
DEPARTMENT OF COMPUTER INFORMATICS

MIROSLAV TRENDAFILOV TRANKOV

APPLICATION OF MACHINE LEARNING METHODS IN TEXTILE FIBER PRODUCTION

ABSTRACT

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The dissertation "Application of Machine Learning Methods in the Production of Textile Fibers" contains 164 pages. The list of references includes 182 (one hundred and eighty-two) sources, of which 37 (thirty-seven) are Internet sources. The list of authors' publications on the topic consists of 4 titles.

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The materials for the defense are available to those interested in the Dean's Office of the Faculty of Mathematics and Informatics, New Building of the University of Plovdiv "Paisii Hilendarski" (bul. 236 Bulgaria Street), every working day from 8:30 a.m. to 5 p.m.

Author: Miroslav Trendafilov Trankov

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Content

INTRODUCTION

Global competition requires companies to cope with dynamic conditions and volatile markets. They need to offer customized products while keeping costs low and bringing products to market quickly. These challenges necessitate the need for investments for the rapid deployment of new technologies. Leading economies, such as Germany, the United States, and China, are responding to these challenges with large-scale initiatives, such as Industry 4.0 (I4.0), the Smart Manufacturing Leadership Coalition, and China Manufacturing 2025. The European Union is also investing heavily to support the modernization of factories. Automation of quality management is a key priority for manufacturers, aiming to optimize processes and minimize losses. Management systems must be continuously developed to cope with the complexity of production processes, changes and to support management decision-making. Industry 4.0 and Big Data technologies offer opportunities for optimization, but their full potential is untapped (Manns et al., 2015). In the textile industry, for example, technological advances improve the efficiency of the production process, but due to unforeseen events and the need to optimize processes, often the governing bodies in factories face challenges in managing the quality and productivity of machines.

The subject of research of the dissertation is the possibilities for automation and optimization of the process for the production of textile fibers. ***The main objective*** of this study is to design and develop a prototype of a software system for automating production planning using machine learning methods. To achieve this goal, the following four tasks are set:

Task 1: Review of research in the field;

Task 2: Design of a software system for planning and optimization of textile fiber production;

Tasks 3: Development of a software prototype of a system for planning and optimization of textile fiber production;

Task 4: Conducting experiments and improving the system.

The first chapter discusses the basic concepts of the studied subject area, examines the models for machine learning and their possible application for improving the processes for the production of textile fibers, and the practical applications are illustrated with examples. In ***Chapter 2***, functional and non-functional requirements, user roles and their main activities are defined, the architecture of the software system and the data model are proposed. The main activities in which machine learning methods can be applied are identified. Based on a detailed analysis, a selection of techniques and technologies for the development of the system is made. ***Chapter 3*** presents the developed prototype of a software system, describing in detail the developed modules for Production Control, Production Organization, Statistics and Machine Maintenance. ***In the fourth chapter, experiments*** from testing the system in Suedwolle Group Italy – Bulsafil S.p.A. branch are described, which prove its applicability for optimization of the production process. The conclusion describes the contributions and outlines the prospects for the development of the conducted research.

CHAPTER 1. OVERVIEW OF RESEARCH IN THE FIELD

In order to outline the context of the present dissertation research, this chapter presents a study of the main stages of the textile production process, classical and modern approaches to the organization and optimization of production and quality control.

1.1. Textile fibre production planning

According to their origin, textile fibers are divided into natural (vegetable, animal, mineral) and chemical (artificial, synthetic) (Stanton et al., 2024). In order to meet dynamic changes in product demand, textile fiber factories must continuously optimize their production processes (Adesina et al., 2024). Production processes in the textile industry are cyclical and follow strictly defined stages (Uddin, 2019): Stage 1. Preparation of the raw material, Stage 2. Spinning and Stage 3. Conditioning and technological storage.

Traditional methods of fabric production include weaving and knitting, using ready-made yarn as raw material. Alternative techniques (e.g. felting, non-woven fabric, binding, stitching and braiding, etc.) produce fabric directly from fibers without the need for yarn. Despite differences in raw materials and processes, all manufacturing techniques involve mechanical actions that can lead to dust and waste contamination. With manual technological treatments, these risks are minimal, but this leads to a decrease in the amount of production.

1.2. Quality control

The high quality of textile fibers requires strict control at every stage of production. Common defects of wool as a raw material, as well as problems arising in fiber fabrication, include thickened sections, short windings, unevenness, hairy yarn, low strength, and impurities (Taher et al., 2016). Leading standards for the classification of defects in yarns are Uster Statistics (Uster, 2024), which measures key parameters (irregularity, knots, thin and thick places, etc.) using comparative data from manufacturers, and the Loepfe classification (Loepfe, 2024), which divides defects into categories (thin and thick places, knots and ties, foreign fibers and materials). The quality of yarn can be improved by electronic cleaning devices, such as YarnMaster ZENIT and Uster Quantum, which generate data that provides the ability to analyze and evaluate their performance.

The textile industry is regulated by numerous ISO standards (ISO 2060, ISO 2061, ISO 2062, ISO 5079, ISO 11505, etc.) that validate physical characteristics, measurement methods, terminology, etc., American Society for Testing and Materials standards for durability, elasticity, color fastness tests, etc., International Wool Textile Organization standards for evaluating the quality of wool yarns.

Efficient fiber production depends on the high quality of the final product and the high performance of the machines. The main objectives of quality control are resource optimization, cost control, improvement and innovation, and waste reduction.

1.3. Classical approaches to production planning

Production planning is key to achieving a company's strategic, financial, and operational goals. It can be seen as a process that manages the allocation of resources (employees, materials, and production capacity) and requires the application of optimization techniques. Planning assists decision-makers in solving long-term, medium-term, and short-term tasks (Swaminathan & Venkitasubramony, 2024).

The planning architectures proposed at the end of the 20th century (e.g. Muscettola, 1994), allow planning of a limited set of aspects, such as time and resource constraints.

Modern planning systems, such as ***the MRP Material Requirements Planning System***, integrate supply chains, decision-making rules, and databases (Chih-Ting Du & Wolfe, 2000), analyze the master production schedule, and plan the necessary components to meet the schedule, automatically adjusting plans as schedule changes occur. The main elements of the MRP system are master production schedule, specification of required materials, inventory data, delivery time, unfulfilled orders, MRP program, results and reports.

Supply chains (Riddalls et al., 2000) are complex logistics systems that convert raw materials into finished products and include suppliers, production centers, warehouses and retail outlets. They can be pull-out (production on demand by a customer) or push-out (production according to forecasts), depending on demand. repair or scrapping, e.g. load a detected defect.

Operational production planning (Olhager, 2013) aims to allocate resources efficiently, minimize costs and shorten delivery times. Achieving this goal requires the development of reliable schedules for order fulfillment. Different approaches (forward, backward, limited/unlimited load) are used to achieve a balance between capacity and customer expectations. such as minimizing the time for completion and waiting for delivery by the customer, maximizing the use of capacities and stocks of unfinished products.

The Advanced Planning System (AMS) is a universal approach to detailed planning. To compensate for the uncertainty caused by factors such as unreliable suppliers and accidents, the PMS uses inventory buffers or response times (Meyr et al., 2013), which requires effective communication between procurement and sales departments.

In a typical supply chain, forecasts are created by different departments (sales, marketing, product management) that develop a consolidated plan (Altekar, 2023). Successful coordination requires effective exchange of order data and flexibility on the part of departments. For the needs of production, contracts, orders and technological maps are developed, and the planning department organizes the production plan after checking the available raw materials and the technological map of the production of the item.

The length of the production cycle significantly affects marketing, production and financial strategies.

The material specification – Bill of Materials (BOM) determines the composition of the final products (Jiao et al., 2000). An important role in determining the production time is played by the stocking department, which coordinates deliveries. The optimal stock level is difficult to determine because it depends on the final product and the production process. which requires balancing the costs and benefits of stockholding. Due to the fact that the ultimate goal of production is to generate profit, the cost of goods sold should also be monitored and measures taken to increase productivity should be taken (Serpa & Krishnan, 2018). Employee productivity examines the added value from each employee to the products sold. Finally, warranty costs should also be taken into account, which are an indicator of the quality of the product. This process can be supported by an integrated information system working on a joint database and a mutual costing system.

The main tasks in the design of production, regardless of the type of product produced, are forecasting (statistical forecasting, inclusion of judgement factors, joint/consensus decision-making), simulation/what-if-analysis and calculation of the safe stock. Complex methods such as extrapolation, econometric models, indices, segmentation, regression model, exponential smoothing methods, stochastic time series models are used to create predictions (Abraham & Ledolter, 2009). It is of particular importance in their preparation to determine their credibility, accuracy and justification, i.e. to verify them. In the second step, information about collected historical data (previous plans) is added to the results obtained, information about the timing of a factor influencing the forecast (e.g. sudden change in the order concerning production) is analyzed and quantities of previous causal influences are calculated. The planning process is carried out in close cooperation between members of the production chain with different roles (sales, production, deliveries, etc.), and in order to obtain a result acceptable to all persons, it is necessary to introduce an effective cooperation process. Due to the many unknowns that may lead to the need for changes (Ballard, 2020), an important step in planning is to perform simulations that allow stakeholders to review and analyze the consequences of running different scenarios. Based on these scenarios, they can plan changes in the technological composition of the item or a decision to produce a new product.

The decision on whether production planning should be carried out from a single level or through a multi-level hierarchy largely depends on the type of production workshop. Production planning aims to generate detailed production schedules for the workshop in a relatively short time interval (Abdelsalam et al., 2023), as popular as a method for visualizing a production schedule is the Gantt chart (Paula et al., 2024). The company must allocate its resources so as to achieve its goals. As a result of the research, mathematical models have been proposed for minimizing costs in production lines (Bowman & Stewart, 1956) and resource costs in short-term planning (Hanssmann and Hess, 1960), batch sizing, and planning and forecasting problems (Eppen & R.K., 1987), managing production under uncertainty arising from the unpredictability of demand or exchange rate trends (Kazaz et al., 2005) and others.

1.4. Methods and tools for optimization and forecasting of production processes

Traditional mathematical models are not effective in the uncertain demand of the global market, which necessitates advanced supply chain management approaches (Pasupuleti et al., 2024). Due to the complexity of supply chains, traditional quality tracking systems in the textile industry face difficulties in traceability. Industry 4.0 creates prerequisites for building smart factories that optimize production, reduce errors and fulfill personalized customer requests. Leading manufacturers are deploying technologies such as virtual and augmented reality, additive manufacturing, big data analytics, industrial Internet of Things, and artificial intelligence (Sahoo & Lo, 2022). Artificial intelligence assists in solving production cases related to quality, maintenance, design, environment and inspection, which stimulates its application in textile production.

Machine learning is a branch of artificial intelligence that allows computers to learn from data without being programmed to perform specific tasks. Machine learning is divided into three main categories: supervised learning (Hastie et al., 2009), unsupervised learning (James et al., 2023), and reinforcement learning (Ernst & Louette, 2024), designed to solve relevant tasks (e.g., classification and regression in supervised learning and dimensionality and clustering in supervised learning). According to the specific task, these categories can be combined to achieve the desired results for specific applications.

Data quality is key to the effectiveness of machine learning. Developers of AI-based programs should be well-versed in data processing mechanisms and data analysis tools, such as Python libraries (Pandas, NumPy, and Scikit-learn), the open-source tool, and the Trifacta Wrangler data preparation platform.

Choosing an effective algorithm to solve a task requires conducting experiments with popular algorithms, such as Linear Regression, Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting, each of which has its own advantages and disadvantages.

Developing machine learning models requires data collection, data preparation, data analysis, and feature design, training algorithm development, model testing, model deployment, as well as continuous model improvement. The accuracy of the model is evaluated by an error matrix that represents the actual results (True positives – TP and True negatives – TN) against the predictive results (False positives – FP and False negatives – FN). Hypothesis testing (Braca et al., 2022) uses samples, with increasing the sample size leading to minimizing Type I (FP) and Type II (FN) errors. Precision (P) and recall (R) evaluate the results (Kossov & Seleznev, 2023): $P = TP/(TP + FP)$, $R = TP/(TP + FN)$.

Neural networks are a powerful tool that allows you to solve complex problems. Artificial neural networks (ANNs) are computational models inspired by the structure and functions of biological neural networks in the human brain (Walczak, 2018). They are made up of neurons organized into layers (input, hidden and output layers). The most commonly used method of training neural networks is the backpropagation method. In this training method, the input data is fed through the network and the outputs of each neuron are calculated until the output layer is reached. Then, to calculate the error, the difference between the grid predictions and the real values (target values) is found. The error propagates back through the network by adjusting the connection weights to reduce the error. This process is repeated repeatedly on the training dataset until the network achieves satisfactory accuracy. There are many types of neural networks specialized for different tasks, including MLP, CNN, RNN, GAN, LSTM.

In textile manufacturing, these artificial intelligence methods can predict defects based on historical data without waiting for the production process to be completed.

Due to their adaptability, neural networks are suitable for production scheduling, production schedule planning (Rohde, 2004), and defect detection (Ayyalasomayajula et al., 2023). Other technologies, such as IoT, big data analytics, blockchain, machine learning, and computer vision, are used in the development of intelligent production planning and control systems (Oluyisola et al., 2022), product tracking (Faridi et al., 2020), predictive quality maintenance, optimization (He et al., 2022), defect detection (Mehta & Jain, 2023; Muminjonovich, 2023; Islam et al., 2024), waste reduction and cost minimization (Reyes et al., 2023), logistics and inventory management (Pasupuleti et al., 2024). They bring a number of benefits to companies, and have the potential to revolutionize the textile industry by helping decision-makers improve production planning and product quality, perform real-time monitoring, optimize the supply chain, forecast demand, minimize costs, and carry out effective management of logistics and production processes, even during unexpected interruptions. Popular ERP systems (e.g. SAP S/4HANA) integrate these process optimization technologies (Abdul-Azeez et al., 2024).

The digitalization of the manufacturing industry and the ability to collect data, machine sensors, and quality measurements creates a huge potential for using machine learning techniques to ensure the quality of the textile fibers being developed, predict equipment maintenance, and optimize the overall production process (Metin et al., 2024).

The use of machine learning algorithms for quality assurance in the textile fiber production process implies familiarization with the specifics of the production process and the equipment used, collection and preparation of data for post-processing, selection of data characteristics, model training. Favorable factors for the application of machine learning are the data provided by the spinning machines, historical data from the quality control systems, developed technological maps, classifications and parameters in the production of yarn of the world manufacturers of equipment in the textile field Uster and Loepfe (Fangueiro & Soutinho, 2010). There are two key problems with data processing: the wide variation of the data and the choice of reporting period. To deal with variations, data averaging is used, with the main parameters being optimal value, specification boundaries and control limits, time interval and current value. The control limits are 10% deviated from the optimal value, and those according to the specification – by 15%. The choice of reporting interval affects the volume of data and the accuracy of the forecasts.

Example 1.A textile fiber production facility collects data from sensors installed on spinning machines. The sensors collect data on temperature, pressure and vibration levels. By training a machine learning model on this historical sensor data and linking it to instances of equipment failure or maintenance needs, the model can learn to predict when problems with the machine are likely to occur. The maintenance team can then schedule preventive maintenance during planned downtime, avoiding costly unplanned failures.

The benefits of predictive maintenance with machine learning in textile fiber production are numerous (Abidi et al., 2022). It allows manufacturers to minimize downtime, optimize resource allocation, extend equipment life, and improve overall production process efficiency. Models analyze sensor data and historical records to predict failures. The process involves data collection and processing, training, and model validation. Conducting predictive maintenance experiments requires the processing of data from sensors installed on machines, records of machine maintenance data, data on actual machine failures, additional information about the production environment, and feature engineering that can improve the model's ability to capture relevant information and prediction accuracy. For predictive maintenance, the Random Forests, SVM and LSTM algorithms are used, and their effectiveness depends on the quality of the data. Other algorithms such as Gradient Boosting, Neural Networks or Bayesian Networks can also be explored based on the specific needs of the textile manufacturing facility.

Example 2. In a textile manufacturing facility, Random Forests can be used to predict machine failures based on sensor readings such as temperature, pressure, and vibration. By training the algorithm on historical data that includes instances of machine failures, the model can learn to identify patterns and indicators that precede failures. It can then predict the likelihood of failure based on real-time sensor data.

Process optimization aims to improve the efficiency, productivity, quality, and overall productivity of the manufacturing process. This requires analyzing the existing process, identifying areas for improvement, and implementing changes to optimize resource use, reduce waste, and increase productivity. process tracking and analysis, defining key performance indicators (KPIs), data analysis and modeling, root cause analysis, optimization strategies, and continuous improvement. Solving the optimization problem (Weichert et al., 2019) requires selecting an appropriate algorithm that can efficiently analyze data, uncover patterns, and provide accurate predictions or insights to optimize the process. The choice depends on the type of data (numerical, categorical), dimensionality and the goals set (regression, classification), the interpretability of the models, the computational requirements of the algorithm. It is good practice to test several algorithms on a specific dataset and evaluate their effectiveness using appropriate validation techniques, such as cross-validation, and compare indicators (such as accuracy, mean square error or F1 score).

Example 3. A textile fiber manufacturer wants to optimize the process parameters for the production of fibers with high tensile strength. They collect data on various input parameters, such as raw material composition, spinning conditions, and processing processes, along with relevant tensile strength measurements for each fiber produced. By training a machine learning model on this dataset, the model can learn the relationships between process parameters and the resulting tensile strength. The model can then offer optimal settings for these parameters, resulting in improved fiber quality and reduced energy consumption.

Machine learning algorithms can also be used to predict and optimize fiber properties. By analyzing various input parameters, such as raw material composition, spinning conditions, and processing processes, the models can accurately predict properties such as tensile strength, elongation, and dyeability of the fibers.

Example 4. A textile fiber manufacturer wants to develop fibers with specific dyeing properties. They collect a dataset containing information on the composition of raw materials, spinning conditions and dyeing test results for various fibers. By training a machine learning model on this dataset, the model can learn the complex relationships between input parameters and fiber dyeing properties.

The application of machine learning methods in textile fiber production brings numerous benefits to the industry - it optimizes textile fiber production, improves quality, efficiency and reduces waste. It enables data-driven decision-making and encourages innovation, ensuring competitiveness in the market.

1.5. Analysis and visualization of production data

Performance analysis in the textile industry can be carried out through a variety of methods and tools.

Statistical process control (SPC) is a quality control method that uses statistical methods to monitor and control processes (Qiu, 2013). The process involves seven steps (Oakland & Oakland, 2007): identifying processes, defining measurable attributes, defining a measurement method, developing a sampling strategy, collecting data, and creating an SPC diagram (e.g., S&P 500). Xbar-R diagram), describing the natural variation and observing the variations of the process.

Manufacturing engineers often mistakenly use SPC and to evaluate process efficiency (PC) (Wu et al., 2009). The SPC monitors the process while the PC measures its ability to meet specifications. The PC compares the results with the specifications and gives a numerical estimate. In order to measure the effectiveness of a process, the process must be "stable", i.e. within the process there can only be variation for a common cause. When a process is "acceptable by default", then SPC can be applied to monitor the process, and when the process does not achieve satisfactory results and does not meet the desired performance levels, then actions can be taken to investigate and implement improvements to achieve the desired performance levels.

The Overall Equipment Efficiency (OEE) assessment is a tool for evaluating production efficiency in industrial environments that brings together three main metrics (Ng Corrales et al., 2020): availability, productivity, and quality. This method is useful for identifying losses in each of these aspects and optimizing the production process.

1.6. Conclusions

In modern textile factories, modern autonomous machines are used, which continuously generate a huge flow of data on various characteristics of textile fibers and the production process. In order to achieve the optimization of the textile fiber production process, it is important to carry out quality control of the produced fibers and predictive maintenance of production facilities, which will lead to improved operational efficiency, increased productivity and cost savings. Despite the wide scale of the textile industry and the variety of items produced, the process of production and sale follows a common process: growing or sourcing raw materials, spinning and producing textile fibers, producing fabric, making fabric products, selling. At each stage of this process, product value is added, which requires reliable and high-quality planning of processes in the production base. This motivates the design and development of a system that allows predicting the trend for the quality of manufactured items, creating information and graphic reports, analyzing trends in the production of machines, optimizing planning schedules, calculating the impact of different settings with an accurate forecast for cleanliness of work, etc.

CHAPTER 2. DESIGN OF A SOFTWARE SYSTEM FOR THE MANAGEMENT OF THE PRODUCTION PROCESS IN A TEXTILE FIBER FACTORY

This chapter discusses the process of designing a software system for managing the production process in a textile fiber factory.

2.1. Technological process

The main stages in the process of textile fiber production are ***cleaning*** of the raw material from impurities, ***mixing and duplication*** of various raw materials, ***combing*** in order to remove short, unfit, dead fibers and impurities, ***spinning*** until a thread of certain qualities is formed, ***winding*** the fibers into suitable cones, ***duplication*** or combining two or more threads, ***twisting them*** in order to increase the resistance and strengthening of the thread, ***conditioning*** the threads by wetting them in order to increase their quality.

In the production process, the manufactured products are processed by many specialized departments: ***Sales, Planning, Global Planning, Raw Materials, Spinning, Combing, Twisting, Duplication, Packaging, Warehouses for Intermediate and Finished Products.*** In each of the departments there are participants with different roles who must have access to different functionalities of the system being built.

2.2. Functional and non-functional requirements

The functional requirements for the production process management system in the factory can be defined in 8 main categories.

Category 1. Monitoring of production processes:

- Monitoring of machines and equipment - current status of machines in real time, output of operational data (speed of operation, current load and availability), identification of states ("active", "stopped" or " under maintenance");
- Analysis of downtime and shutdowns - generation of a "Stop Chart" with the reasons for stops, their frequency and duration, historical tracking of the reasons for shutdowns for optimization;
- Monitoring of key indicators - visualization of the efficiency of the machines, productivity and quality of the manufactured products.

Category 2. Production planning:

- Creation of production plans - generation of planned tasks based on current requests, available raw materials and capacity, support for flexible scheduling with the possibility of real-time adjustments;
- Batch management - automatic resource allocation for each production batch and tracking the production cycle of each batch;
- Coordination through the production calendar - visualization of all tasks and appointments in the production calendar, the ability to set up notifications for critical points and tasks.

Category 3. Control and maintenance of equipment:

- Preventive maintenance scheduling - creating a schedule for regular maintenance of equipment based on wear and load, automatically sending notifications about upcoming maintenance;
- Repair management - tracking the condition of the machines and registering the necessary repairs, analyzing the causes of damage and wear;
- Monitoring of maintenance efficiency - generation of reports on maintenance time and costs, visualization of statistics on the recurrence of problems.

Category 4. Quality Control:

- Analysis of production – analysis of key quality indicators of manufactured products, creation of reports for deviations from standards;
- Defect monitoring - tracking the causes of defects and their share in the production and generating recommendations for corrective actions.

Category 5. Analysis and optimization:

- Use of artificial intelligence methods - generation of predictive models of productivity, equipment wear and tear and resource needs, analysis of the efficiency of production lines;
- Process optimization - suggestions for optimal allocation of resources based on historical data and current conditions, evaluation of alternative production strategies.

Category 6. Integration with ERP systems:

- Automatic synchronization of data on stocks, requests and finished products between the ERP platform and the system;
- Generate integrated reports that combine operational and financial data for analysis.

Category 7. User Interface:

- Inclusion of dashboards, graphs and diagrams for easy process tracking and interactive elements to access modules;
- Role-based access (operator, scheduler, administrator, manager) to specific modules and functionalities;
- Multilingual support.

Category 8. Session Management:

- Multi-user support;
- Registration of user actions for traceability and security.

Aspects of the system that are not related to the textile fiber production process, but are important for its efficiency, are performance, security, reliability, usability, compatibility, scalability, maintenance and updates, regulatory compliance.

The system must provide performance by processing data from sensors and databases in real time, fast analysis (1-2 minutes per 1 million records), and support for large volumes of data (up to 10 TB), while ensuring scalability without performance loss. Security requires the introduction of role-based access, data encryption, security monitoring and protection against attacks (SQL Injection, XSS, CSRF), as well as secure password management. Reliability is guaranteed through 99.9% uptime, regular backups, and fast crash recovery (1 hour). For convenience, it is important to provide an intuitive and multilingual interface, easy navigation and dynamic visuals. Compatibility is achieved through integration with ERP and BI systems (REST API, SOAP), support for various databases (PostgreSQL, MySQL, MSSQL) and access from different devices. Scalability should be ensured by horizontal and vertical scaling. Support and update requirements are seamless updates, built-in diagnostics, and automatic notifications of problems. The system must comply with GDPR, ISO 27001 and ISO 9001 regulations.

2.3. Identification of key textile fibre production activities where AI methods are applicable

AI can automate and optimize various production processes, including:

- Performance analysis - predicting the load on machines and recognizing anomalies;
- Optimization of production lines - dynamic distribution of tasks and optimization of the work flow;
- Quality control and prediction - identification of defects by computer vision, analysis of the causes of deviations, defect prediction and spectral analysis;
- Maintenance of machines - forecasting of failures and optimization of maintenance costs;
- Automatic creation of reports.

2.4. User roles and rights

The main roles in production are ***Production Operator, Production Planning Specialist, Support Administrator and Quality Manager***. Each role must have access to specialized functionalities in the system, and a user with a given role can have different rights to a given object or functionality. For **user rights,** 5 options can be distinguished: Read***,*** Write***,*** Update***, Analyze*** data, and Execute specific actions.

Production operators monitor and manage processes in real time using modules for monitoring and analysis of key indicators. Their main activities include:

- Monitoring of machines - Reading data on the current status of equipment;
- Shutdown Analysis - View and analyze shutdown graphs to identify the causes and evaluate the performance of machines;
- Spindle Analysis - Analysis of spindle data to detect accidents and deviations for preventive maintenance.

A production planning specialist is responsible for creating and managing the production plan, batches, and coordination of activities. Its main activities include:

- Creation/modification of a production plan - determination of schedules and resources for each batch;
- Update of work plans - adjustment of plans according to availability and goals;
- Production calendar review - check for compliance of plans with the general schedule.

The administrator is responsible for planning and managing equipment maintenance, including condition monitoring and defining preventive tasks. Its main activities include:

- Maintenance scheduling - creating and recording tasks for regular technical support;

- Sending notifications - automated or manual notifications for upcoming tasks or emergencies;
- Performance monitoring - checking the execution of tasks according to the schedule.

The Quality Manager is responsible for quality control, process optimization, and performance analysis. Its main activities include:

- Collection of quality data - access to detailed statistics on quality indicators;
- Batch quality analysis - detailed analysis to identify deviations, defects and trends;
- Process optimization - implementation of improvements through analytics and machine learning, incl. adjustments to standards.

2.5. Application architecture

The system is appropriate to be built on a standard ***multi-layer architecture*** (Fig. 1), which separates from each other ***the layers for data storage, the main business logic and the user interface*** for accessing the functionalities and presenting the data. This architecture can be applied in the construction of both desktop and web applications.

The multi-layer architecture offers significant advantages, such as modularity allowing for clear responsibilities of each layer, flexibility and scalability for easy addition and modification of functionalities, reusability of components, simplified testing and maintenance, and improved security through control of individual layers. The application uses ***an enterprise ERP system*** as the main source of data (machines, orders), ***a local database,*** data from Uster and Loepfe machines (by accessing ***Uster and MillMaster SQL servers***). The Business Logic level includes components such as ***Planning, Forecasting, Analytics***, which use the created data models from the ***Data Model component.*** Access to the data layer is provided only through the functionalities provided by the ***Data Access component***, and ***Planning***, ***Forecasting*** and ***Analysis*** communicate with the level modules for the representative layer, which provides a user interface and data visualization components (***Dashboards*** and ***Charts***).

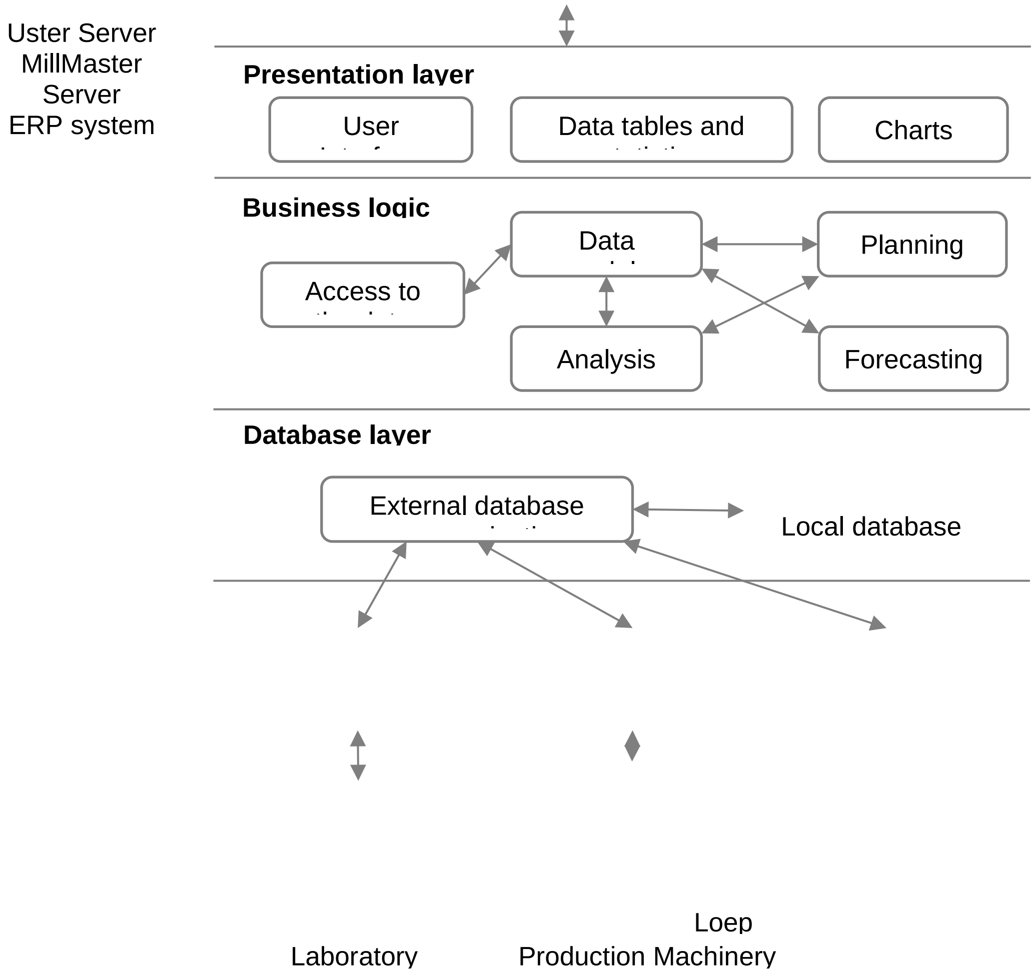


Figure 1. Application architecture

2.6. Data model

The database of the application stores data about machines, production processes, customers, orders, warehouses, workers, defects, etc. The main entities of the database are the ***tables Customers*** (customer data), ***Product*** (product data), ***Machine*** (data for production machines), ***Order*** (data for customer orders), ***Batch*** (data on batches of manufactured products and machines used), ***Warehouse*** (data on warehouses and batches stored in them), ***Process*** (data on processes and machines involved in them), ***Worker*** (data on workers), ***Defects*** (data on defects that occurred in the production process) and ***StopEvents*** (data on interruptions that occurred in the production process). The main entities with some of the attributes and the relationships between them are illustrated in Figure 2. It is important to note that additional tables and attributes are created when the database is implemented.

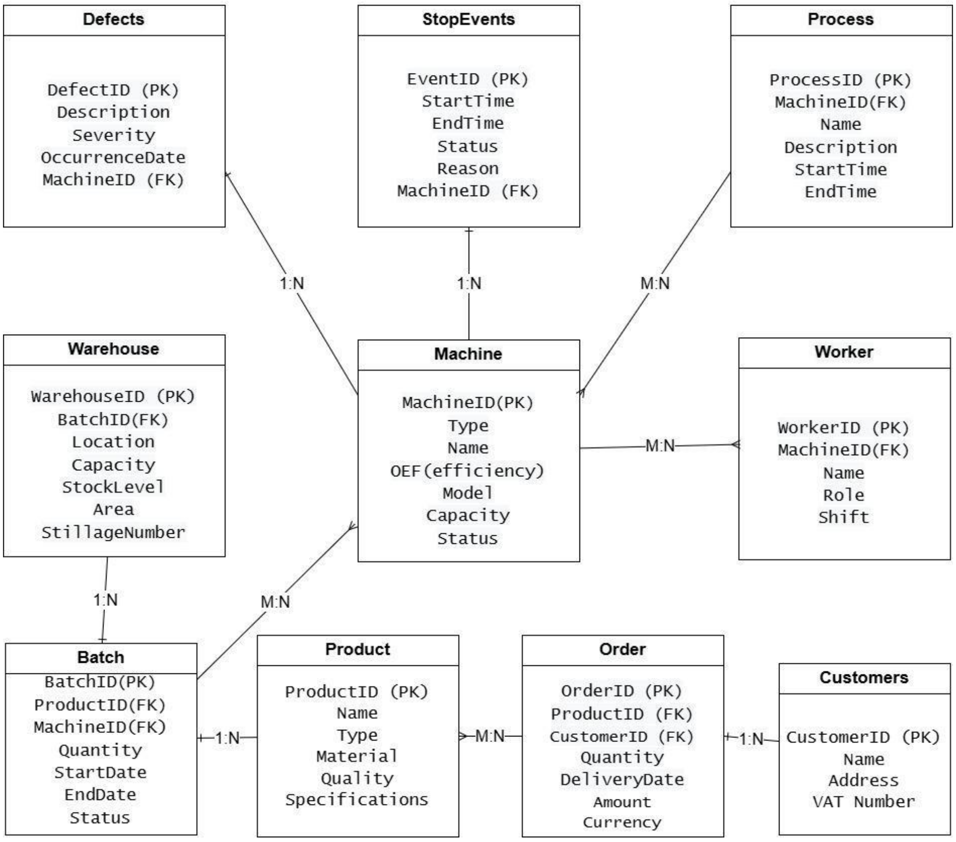


Figure 2. ER Chart

2.7. Machine learning and textile fibre production

In complex production environments where multiple processes are executed simultaneously, ***optimal task planning*** is key to efficiency and profit. To achieve this, it is necessary to implement decentralized planning, which allows the use of the expertise of the staff from each department and their current knowledge of the state of the production floor. which sets out the overall objectives and constraints. The factors to be taken into account when making decisions are the amount of overtime and additional shifts, the current availability of items in the production chain and agreements with suppliers for the purchase of raw materials. The Global Plan provides information on seasonal stocks and delivery deadlines, allowing for longer-term and strategic planning.

The production planning process begins with *the construction of a model* that reflects the specific production processes and material flows, including the use of machine learning methods. This is followed by the *extraction of the necessary data* from ERP systems, global and marketing planning. Based on this data, *scenarios are generated* that reflect possible assumptions and expectations for production. *generation of an initial production schedule* that can be *analyzed and adjusted interactively*. After *approval of the best-case scenario*, the schedule is *transferred for execution* to the MRP module, the ERP system for plan execution (optional step), the transport planning module *and updated* when events occur, such as new orders or failures.

The planning model includes structural and situational data, such as line location data, material specification, resources, suppliers, machine setup matrices, and schedules (calendars). The application can provide performance analysis of production by identifying areas for improvements and optimizations. For example, if the analysis shows that a particular production line regularly produces a higher scrap rate, the system may suggest changes to machine settings or production processes. This not only increases the quality of production, but also optimizes the use of resources.

Grouping machines by functionality facilitates planning and ensures uniform productivity. An important task in production planning is to determine the ***production period*** and the number of work shifts for which an item will be produced in the machine passages. case. To achieve optimization, it is important to determine the factors affecting production and analyze delays. For example, the main technological characteristics of wool are thickness, number and length of fibers, composition, metric index, number of spindles, spinning technology, drawing speed and twisting direction (Naumann, 2014). Suitable algorithms for solving this problem are regression algorithms (Linear Regression, Decision Trees, Random Forest, etc.), through which the number of shifts can be predicted, taking into account the order quantity, the kilograms of carrot generated, the length of the fiber, the color, composition and article group, the start date of production. Additional factors are types and number of machines, processing technology and accidents.

Among the most common are thickened sections, short windings, thick and thin spots, hairy yarn, low strength, poor braiding, and the presence of external impurities (Taher et al., 2016). To ensure ***high yarn*** quality, it is important to control key criteria such as coefficient of variation, number of thin and thick places per km. textiles, number of nodes/clusters per km. textiles, tensile flexibility, strength, ruffled thread, percentage deviation from the baseline values. For each of the characteristics in the production of a specific product, control limits can be defined to trace deviations or anomalies in the production process.

The process of ***predicting the quality of textile fibers with machine learning methods*** begins with the selection of input data and factors, determining the independent variables (factors) and the dependent target variable. The data is then divided into two sets: training data and testing data, usually in a ratio of 80:20. which is then used to predict on the test data. The accuracy of the predictions is evaluated by comparing the predicted and actual values from the test data. When predicting the quality of textile fibers, characteristics such as uniformity, strength and others can be used as a target variable, and the rest of the characteristics are used as factors. Correlation analysis can help identify and eliminate dependencies. Machine learning libraries such as Random Forest in Python are used to implement predictive models. To evaluate the accuracy of the prediction, metrics are used to compare the true and predicted values. The mean square error (MSE) measures the mean of the squares of differences, with lower values indicating better accuracy. The square root of the mean square error (RMSE) is another commonly used metric. The mean absolute error

(MAE) measures the average absolute difference between predicted and real values. The coefficient of determination (R^2) indicates the degree of efficiency of the model, with values close to 1 indicating that the model is effective. MAE, MSE, and RMSE are easier to interpret when the units of measurement are the same as those of the input data. R^2 shows how well the model describes the variations in the data.

2.8. Selection of techniques and technologies for work

Python was chosen for the backend to build the web application due to its popularity, rapid development, and machine learning libraries, such as NumPy, Pandas, Scikit-learn, and TensorFlow (Raschka et al., 2020). The client part will be built with the standard languages HTML, CSS and JavaScript, and the Bootstrap framework will be used for responsive design, ensuring good work on different devices. For integration with various databases, incl. MSSQL, Oracle DB, MySQL and PostgreSQL, the SQLAlchemy library will be used. The application will be able to integrate with ERP and BI systems, as well as with specialized databases of Loepfe and Uster used in the textile industry. In order to quickly build high-performance APIs and real-time query processing, the Flask framework was chosen (Idris et al., 2020).

2.9. Conclusions

The proposed application architecture and data model provide a solid basis for the development of a production process management system based on modern technologies and methods of artificial intelligence, which will allow for effective management of textile fiber production, increasing productivity and quality of production, as well as optimizing the use of resources.

CHAPTER 3. SOFTWARE IMPLEMENTATION

The developed application integrates 4 key functions in the production process of a textile fiber factory - Production Control, Production Organization, Statistics and Machine Maintenance. For easy and intuitive navigation, a side menu is implemented in the application, accessible from each module. A number of good practices have been applied in the implementation: division of responsibilities between HTML, CSS and JavaScript for structure, styles and interactivity; adaptability for optimal display on different devices; caching via CDN for fast loading of resources; dynamic HTML loading with Jinja2 templating engine; and security provided by Flask against XSS attacks. Depending on the user role and other criteria, the menu contains different items.

3.1. Control of production

The ***Production Control*** Section provides opportunities for effective monitoring and management of production processes. It provides tools for monitoring and control of machines (Machines module), customized dashboards for monitoring key performance indicators (My Dashboard module), detailed analysis of downtime and opportunities (Downtime Diagram module) and spindle performance evaluation and preventive maintenance (Spindle Analysis module).

The *Machines* module provides users with the opportunity for effective monitoring of production machines in real time. It visualizes dashboards that allow tracking of the machines used in the different stages of the production process – Card, Draw Frame, Roving and Ring. For carding machines, data of the processed batch is visualized, while for combining machines (Draw Frame), roving (Roving) machines and spinning machines with rings (Ring) operational status and batch numbers. Visual signaling with colors and icons allows you to quickly identify the status of each machine. UI/UX design is focused on clarity, navigation, and access to real-time data, using best practices, such as category grouping, responsive design, real-time updates, color coding, and modular component structure. The loading of all machine data, as well as the update of statuses, is done in real time by calling server logic via JavaScript. An additional functionality of the module is the provision of detailed information about each machine in a separate window, incl. data on the production produced, the speed of the spindles and details of the item. Data is loaded only when a machine is selected to optimize traffic, and the window is automatically positioned according to the screen size.

The *My Dashboard* module provides managers with the opportunity for operational management by tracking key production indicators in real time. It allows for quick intervention and optimization of processes by showing the efficiency and production of the Cards, Draw Frame and Speed Frame machines, as well as the reasons for their shutdown Chart.js s. which provides the ability to draw interactive pie charts, bar charts and KPI indicators, loaded dynamically in real time.

The *Downtime Chart* module visualizes the operating hours of machines by showing their status over a certain period, usually a shift. The graph uses color coding to indicate different states: green for normal operation, red for stopping, yellow for delay, dark red for alarms, and light blue/purple for specific operational states. The timeline at the top of the graph shows the length of downtime, and users can choose specific machines for analysis. This module is useful for identifying shutdown patterns, optimizing maintenance, and minimizing downtime. The data is extracted from the database's Machine and StopEvents tables, and the D3.js's JavaScript library is used for visualization.

The *Spindle Analysis* module provides users with statistics and history of spindle operation, which allows for efficient management and maintenance. The overview view is presented in a tabular format, where data on spindle breaks are organized by machines and departments, and quantitative values show the frequency of interruptions and events. including date, duration, type of interruption and status of the machine. The module is useful for identifying trends and outage patterns, planning preventive maintenance, analyzing and optimizing production processes, improving product quality, and evaluating equipment efficiency.

3.2. Organisation of production

The ***Production Organization*** category provides tools for effective planning and management of production processes, including modules for batch tracking and management (Batch Tracking module), resource, time and capacity planning (Planning module), creation of detailed work plans (Batch Work Plan module), complete batch management (Batch Manager module) and organization of activities through a calendar (Calendar module).

The *Batch Tracking* module provides users with a detailed overview and allows management of production information for each batch. It allows easy tracking of progress, identification of machine problems and optimization of production processes. Batch information includes code, quantity, item, composition, color, notes, delivery date and customer, batch status in the spinning process and progress towards completion. measured in kilograms. A detailed table provides information about the machine, department, start and end dates, assigned amount of material to each machine, average production speed, quantity produced in kg., equipment efficiency, working and stop times, doping, interruptions, weight, yarn number and functional/technical downtime. The module uses the Batch, Machine and BatchMachine tables. The module has implemented additional functions such as search by code and filtering by status.

The Planning *module* generates a Gantt chart that graphically represents the plan of production batches and their time frames. Each horizontal line represents a separate machine, and the different colors and blocks on these lines indicate different production batches. Resources. This kind of planning is especially valuable in complex manufacturing environments where timeframe accuracy and resource planning are essential. The module uses the Machine, Batch and BatchSchedule tables and has server code to load the production schedule and a function to predict end dates for implementation. To predict end dates, linear regression trained on historical data for completed lots is used. The model predicts an end date based on start date and quantity, returning the result in JSON format.

```
from sklearn.linear_model import LinearRegression
import numpy as np
@app.route('/predict_end/<int:batch_id>')
def predict_batch_end(batch_id):
    batch = BatchSchedule.query.filter_by(BatchID=batch_id).first()
    # Historical data for forecasting
    past_batches = BatchSchedule.query.filter(
        BatchSchedule.MachineID == batch. MachineID,
        BatchSchedule.Status == 'Completed'
    ).all()
    X = np.array([[b.StartDate.timestamp(), b.Quantity] for b in past_batches])
    y = np.array([b.EndDate.timestamp() for b in past_batches])
    model = LinearRegression()
    model.fit(X, y)
    # Predicting the new end date
    predicted_end = model.predict([[batch. StartDate.timestamp(), batch. Quantity]])[0]
    batch. PredictedEndDate = datetime.fromtimestamp(predicted_end)
    db.session.commit()
    return jsonify({'predicted_end': batch. PredictedEndDate.strftime('%Y-%m-%d %H:%M:%S')})
```

The *Batch Work Plan* module allows operators to monitor and manage the different stages of the production process for a specific batch and adjust the production parameters according to customer requirements and production standards. It visualizes in tabular form detailed information about a specific batch (unique code, quantity, item, color, delivery date and customer) and the progress of production stages (carding, drawing and spinning), as well as the amount of material intended for each phase and yarn parameters (fineness, rotation and direction). For each stage, it is shown whether it is completed or in progress.

The *Calendar* module provides users with quick visual information about the availability of workers and makes it easier to plan staff according to production needs. It shows the planned shifts for each day of the month, indicating the number of shifts with color coding for normal working hours and special conditions. The calendar indicates special events that require attention (audit, important delivery, etc.). It allows production specialists to plan efficient employment of operators, take into account the logistics of production and ensure that there is no shortage of personnel. For the implementation of the module, tables for shifts and special events have been created.

3.3. Statistics

The ***Statistics*** category provides detailed statistical analyses and reports on production efficiency, which are essential for making informed management decisions. It includes tools for creating standard reports, detailed statistics for individual departments, graphs for data visualization and climate reports for analysis of the working environment.

The *Standard Reports* module provides the ability to filter and analyze the reasons for the shutdown of machines in a certain department for a selected period. Users can generate reports that contain values of key indicators, such as reasons for shutdown, their frequency and duration, distributed by shifts, machines or periods. as well as print and export buttons.

The *Detailed Statistics* module measures efficiency and production parameters by visualizing data on total equipment efficiency in percentages, production in kg, outages, electricity usage, current temperature and humidity values, as well as trends from the previous year. This data helps to identify problems and optimize processes.

The *Graphs* module (see Figure 3) visualizes data and forecasts using SPC. It provides the ability to create control charts for various criteria, visualize historical data, control boundaries and forecasts. identifying trends and anomalies, detecting problems preventively, and maintaining high quality and efficiency. At the time of implementation of this module, the Exponential Smoothing method gives the best results (93-95% accuracy) due to its ease and reliability, outperforming other machine learning methods (less than 90%).

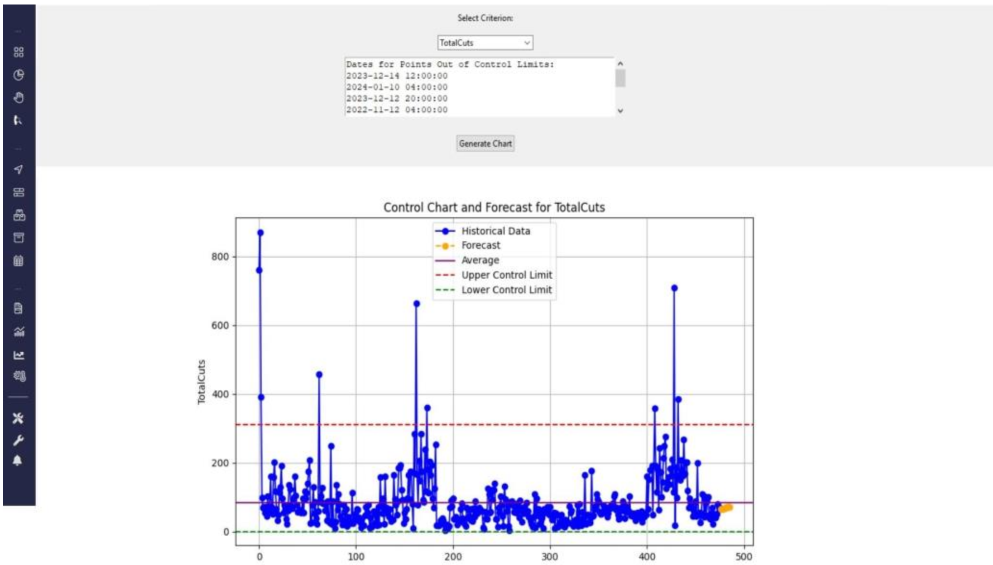


Figure 3. Screenshot of the Graphics module

The *Climate Reports* module visualizes a dashboard with climate control data and production data that are critical to ensuring optimal conditions in textile production. The dashboard visualizes current temperature and humidity data, historical temperature graphs by machine/department, frequency of outages, comparison of average temperature and humidity for two days and a table of details for machines. identification of trends and anomalies and optimization of production conditions.

3.4. Maintenance of machinery

The ***Machine Maintenance category*** includes modules for maintenance planning, preventive maintenance and automatic notifications. It is important that the modules in this section are integrated with the production processes in order to minimize interruptions in operation.

The *Maintenance Planning* module generates schedules for routine and scheduled maintenance that reduce downtime. The interface provides an overview of maintenance, including an overview and dedicated sections for mechanical and electrical maintenance. The scheduling calendar visualizes planned, completed and unfinished tasks, and the color coding shows the status of tasks. week, day and agenda, as well as use filters for a detailed view of tasks by parameters. This module helps to create a clear plan for upcoming activities, monitor implementation and respond to deviations in a timely manner.

The *Preventive Maintenance* module allows planning and management of preventive maintenance of machines by using a color-coded calendar view to visualize the status of activities (green – completed activities, yellow – forthcoming, red – unfulfilled). In the future, the integration of AI will allow the analysis of production data and the prediction of potential problems, which will allow preventive responses and reduce downtime. It involves extracting and presenting maintenance data, creating a fault prediction model, applying the model to current data, and visualizing forecasts.

The *Automatic Notifications* module allows you to manage email notifications for changes in production batches. It provides functionality for adding and removing email notifications, as well as for sending notifications when a batch is changed, including information about the change and the person who made it.

3.5. Conclusions

The developed application demonstrates an integrated approach to the management of textile fiber production, covering all key stages and aspects. The modular approach to component design makes it easy to expand and maintain. The app is a valuable tool for managing a production process in a textile fiber factory, aiding in decision-making, process optimization, and improving production efficiency. The use of modern technologies and methods for data analysis, incl. Machine learning and statistical process control, makes the application a powerful and effective tool for managing the production of textile fibers.

CHAPTER 4. EXPERIMENTS

The developed software system has been implemented in "Suedwolle Group Italy – Bulsafil S.p.A." for planning the production of worsted yarns. The experiments with the implemented system were carried out by four groups of employees: production operators, who control the machines and respond to daily problems; production planning specialists responsible for planning and optimization; quality managers monitoring quality and efficiency; and maintenance administrators responsible for equipment maintenance.

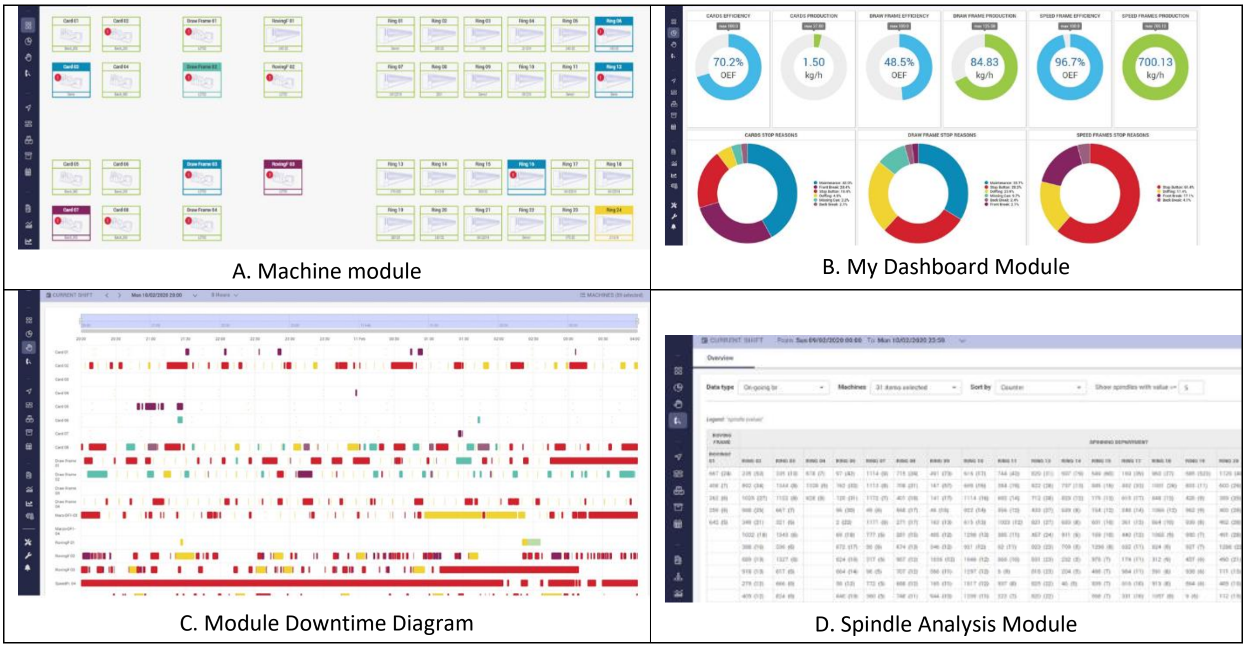
4.1. Control of production

The implementation of the *Machines* module allows monitoring of production equipment and supports the work of all departments in the company. It provides real-time monitoring capabilities for machines, allowing operators and maintenance administrators to receive information about the status of machines, including damaged or in need of maintenance. redirecting resources and adjustments to the schedule, and quality managers to identify frequent problems and look for patterns to improve processes. The module visualizes a dashboard with information about machines from different stages of production, giving an indication of problems that have arisen. Color coding indicates the status of the machines. This helps to respond quickly to failures, optimize the production process, reduce downtime and errors, and improve communication. Figure 4.A shows information about the 8 carding machines, 4 drawing machines, 3 quick drawing machines and 26 spinning machines used in the company, of which 13 had problems.

The My Dashboard module has been implemented to enable optimization decisions, data-based review of key production indicators in real time. Production specialists and operators can monitor in real time which machines have a loss of performance and take corrective action, administrators can analyze the causes of shutdowns, and quality managers can monitor for recurring problems. The module visualizes pie charts for efficiency and machine production, as well as graphs with the reasons for shutdowns. From the graphs visualized in Figure 4.B, it can be seen that the percentage of efficiency of the machines for carding, drawing and fast drawing is 70.2%, 48.5% and 96.7%, respectively, and their productivity is 1.50 kg/h, 84.83 kg/h and 700.13 kg/h. The most common reasons for stopping carding and pulling machines were maintenance (42.0% and 33.7%), while in the case of fast pulling machines, the most interruptions were due to pressing a stop button (61.4%).

The *Downtime Diagram* module visualizes the operating time of machines, which data on the frequency and duration of downtime and allows analysis of outages. Operators and maintenance administrators use the module to quickly identify and respond to problems, production specialists to monitor efficiency and optimization, and quality managers to analyze the impact of downtime on production. from different stages of production, showing interruptions due to technical problems, delays and specific conditions. The color coding and block length indicate the length and frequency of downtime. The module helps to optimize production by redirecting the load and better planning, allowing detailed analysis of each machine and supporting the rapid identification and troubleshooting as well as the long-term optimization of processes.

The Spindle Analysis *module* visualizes statistics on spindle operation and a detailed chronology of events for a selected spindle. The table (see Figure 4.D) shows spindle statistics in 23 machines for the period 9.02.2020-10.02.2020, with each cell containing numerical values reflecting interruptions, defects and other indicators. Defects signal potential problems, such as technical malfunctions or technological adjustments. In the generated table, this is the case with spindle 685 in the RING 19 machine, for which 523 interruptions were reported. The analysis helps production specialists and support administrators identify weak points and plan preventive measures.



A. Machine module

B. My Dashboard Module

C. Module Downtime Diagram

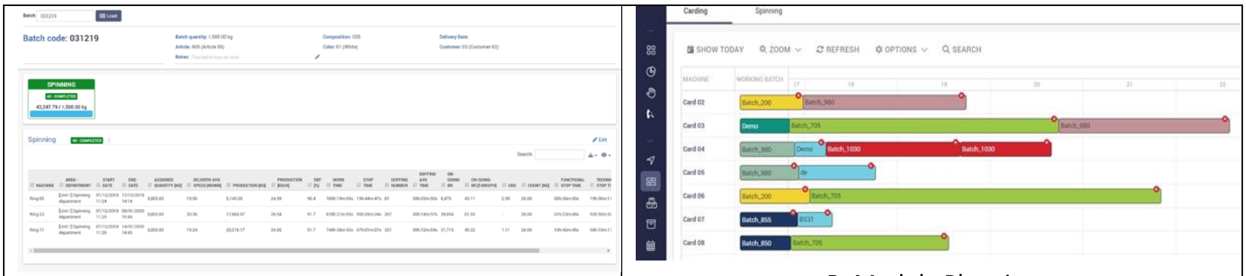
D. Spindle Analysis Module

Figure 4. Screenshot of modules in the Production Control category

4.2. Organization of production

The implementation of the *Batch Tracking* module allows for a detailed overview of the production information for a specific batch (see Figure 5.A), allowing production specialists to monitor the progress of batch production, identify problems, optimize resources and plan maintenance. It visualizes basic batch data, production progress and information about the machines working on the batch. Production specialists to compare speeds and efficiency, analyze the causes of downtime and identify low-efficiency machines and take corrective action. They can keep track of the quantity produced and the remaining quantity to ensure that delivery deadlines are met.

The Planning *module* allows operators and production professionals to visualize a Gantt chart (see Figure 5.B), which visualizes data for batch production periods and allows for problem identification (red dots), capacity analysis, resource optimization and time monitoring. Identify spare capacity and expected loads, allowing tasks to be rerouted and machine utilization optimized. Its use improves production planning and control, minimizes downtime, increases efficiency and ensures timely response to delays.



A. Batch Tracking Module

B. Module Planning

Figure 5. Screenshot of modules in the Production Organization category

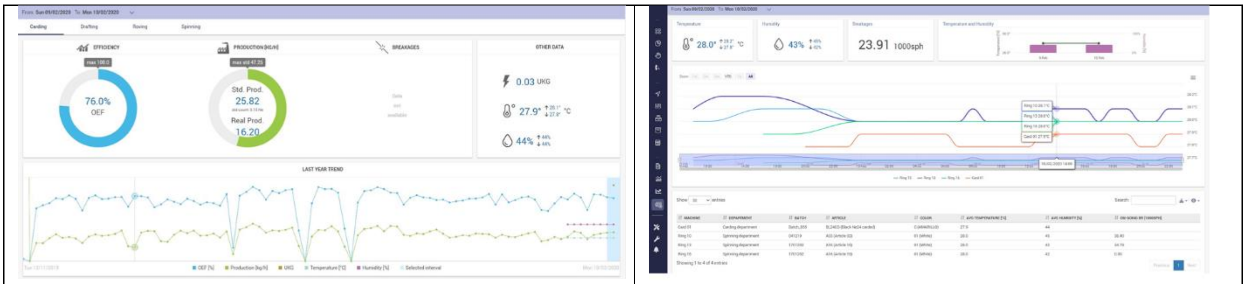
The use *of the Batch Manager* module allows operators to monitor and manage the production stages. It visualizes detailed information about the batch (code, customer, quantity, item and color of the batch, stage status, quantity, fineness, rotations and direction of the yarn), the progress of work and allows control of parameters.

The *Calendar* module allows operators and production professionals to view worker availability and supports occupancy planning. It shows a department schedule with scheduled shifts for the month, an indication of the number of shifts and color coding, as well as special events indicated by a red line.

4.3. Statistics

The Detailed Statistics *module* (see Figure 6.A) provides production and maintenance managers with data to measure efficiency and production parameters. It visualizes data on equipment efficiency, compares standard and actual production speeds, displays energy consumption, temperature and humidity, and presents historical graphs for key indicators. dynamics of production and climatic parameters, signaling problems in the process, compliance with planned norms and optimal climatic conditions. Trend charts help detect long-term patterns. In this way, the module helps to identify problems, optimize processes, improve efficiency and productivity, ensure optimal climatic conditions and plan improvements.

The Climate Reports *module* allows production professionals and maintenance administrators to monitor climate data and its impact on production. It visualizes data on key climate indicators such as average, minimum and maximum temperature and humidity values, frequency of outages, historical graphs of climate change and detailed data on machines (see Figure 6.B). the requirements for optimal performance, monitoring the correlation between climate change and interruptions, and identifying potential problems. In this way, the module helps to regulate air conditioning systems, minimize interruptions and ensure high quality and efficiency.



A. Module Detailed statistics | B. Module Air Reports

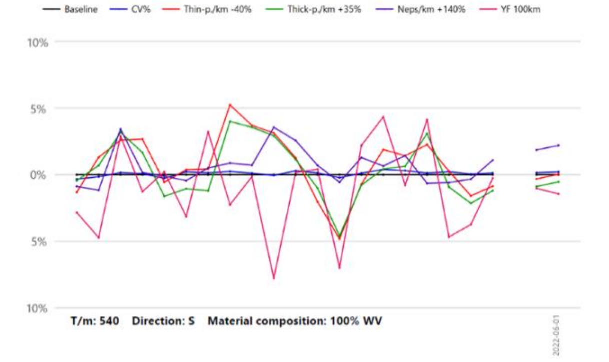
Figure 6. Screenshot of modules in the Statistics category

4.4. Forecasting the production period of an article

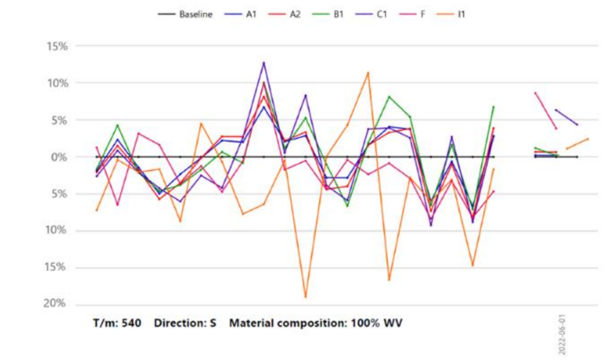
The forecasting of the production period for an item(article) was carried out with data provided by "Suedwolle Group Italy – Bulsafil S.p.A.", an international company with many years of experience in the production of worsted yarns. The preparation of the training data involved three sub-processes: synchronization of data from different ERP systems, extraction of the necessary training factors, and serialization of the data. Problems that arose during the preparation (old software applications, insufficient control) stimulated the development of new software solutions. As a result, 26,279 data records meeting training requirements were created. The Decision Trees and Logistic Regression algorithms were used to predict the production period. Initial tests on 5710 records with 5 characteristics and 15 days of production showed low accuracy (25% for Decision Trees and 22% for Logistic Regression). Analysis of the data revealed significant variations in production days (1-20) and kilograms produced (100 kg – 50 tons), making it difficult to train models. To reduce variations, a data aggregation technique was applied, with production days averaged ±1 day and kilograms produced with an accuracy of ±500 kg. As a result of the grouping, the accuracy increased to 61% for Decision Trees and 59% for Logistic Regression. Using a larger number of records (26,279), one item group and 15 days of production with an accuracy of ±1 day, the accuracy reached 90% for Decision Trees and 89% for Logistic Regression, which gives hope for even more effective forecasts when optimizing the parameters of the applied algorithms.

4.5. Quality control in the production of textile fibres

This experiment aims to create a model to predict deviations in yarn quality for the 21st day using quality data from the previous 20 days. A standard methodology was used to conduct it, and the data were collected with Uster and Loepfe devices. Yarn parameters such as CV%, Thin, Thick, Neps, YF (Uster) and A1, A2, B1, C1, F, I1 (Loepfe) for one item are analyzed. 4 algorithms were tested (Linear Regression, Logistic Regression, Decision Tree, Random Forest), with 80% of the data used for training and 20% for testing and evaluating the models. Figure 7 shows the studied parameters and their deviation from the baseline values within the production process.



A. 21-day chart tracking quality through Uster criteria



B. 21-day chart tracking quality through Loepfe criteria

Figure 7. Results

The two experiments were conducted under identical production conditions, with the difference being in the data set used and the frequency of data reading (5 minutes in the first experiment and 2 minutes in the second experiment). Although machines can report defects every second, minute, hour, or day, experiments are focused on predicting the values of each criterion individually. Data from Uster and Loepfe instruments cannot be combined due to differences in measurement methods and specific criteria of each manufacturer. Each experiment was conducted with two datasets from Uster and Loepfe, each with 14,400.5 characteristics and reported within 20 days at 2-minute intervals, using 4 algorithms: Linear Regression, Logistic Regression, Decision Tree and Random Forest. The best results were achieved with the Decision Tree algorithm (see Table 1).

Table 1. Percentage success rate in predicting the 21st day with 14400 records

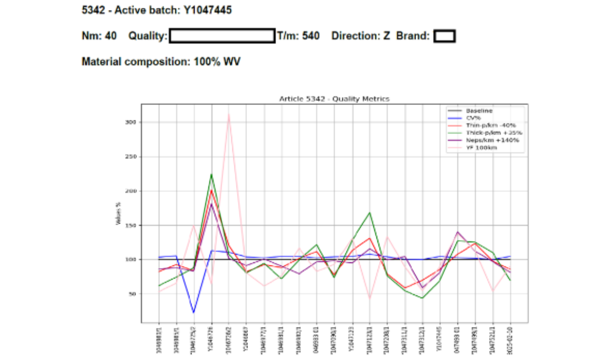
Algorithm	Criteria									
	Uster Appliance Data				Loepfe appliance data					
	CV%	Thin-p./km 40%	Thick-p./km +35%	Neps.km /+140%	YF 100km	A1	A2	B1	C1	I1
Linear Regression	82%	76%	81%	55%	48%	81%	83%	85%	85%	83%
Logistic Regression	85%	81%	84%	60%	51%	82%	86%	89%	90%	82%
Decision Tree	91%	90%	93%	64%	58%	89%	91%	92%	93%	87%
Random Forest	80%	79%	86%	57%	47%	79%	81%	88%	87%	81%

4.6. Automated report generation and notification

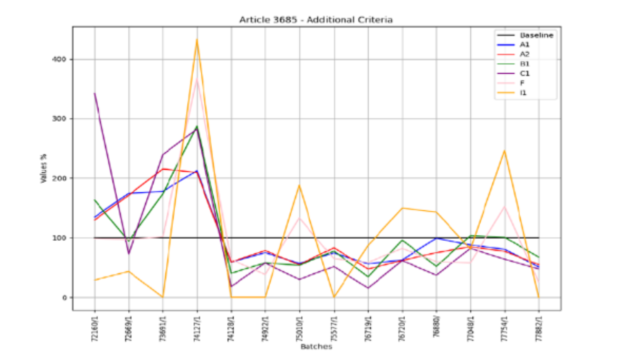
In order to provide access to quality and visual information about production, a functionality has been developed for automatic generation and distribution of reports via e-mail.

The developed functionality generates reports for each production location, replacing manual analysis of metrics and speeding up decision-making and allows comparative analysis of quality between different locations. The reports contain graphical visualizations (see Figure 8) of quality indicators for each batch produced, allowing the analysis of deviations from the baseline values of parameters such as Neps/km, Thin-P/km, etc., and the identification of potential problems in machine settings or raw material quality.

The process is automated and includes data collection, analysis, visualization, generation of PDF reports, and email distribution. Linear regression and LSTM were used to conduct the experiments, which show high accuracy and allow for effective prediction of qualitative indicators.



A. Graph of primary criteria from an automatically generated report



B. Graph of additional criteria from an automatically generated report

Figure 8. Generated reports

4.7. Conclusions

The experiments carried out prove the applicability of the proposed solutions for optimizing production processes in a textile fiber factory. The developed solutions can be implemented in other companies, and for this it is necessary to change the data sources used.

CONCLUSION

Within the framework of the dissertation research, the tasks set were solved and the main goal of the dissertation research was achieved, namely the design and development of a prototype of a software system for automating production planning using machine learning methods.

The main contributions of the dissertation can be characterized as scientifically applied and applied.

Scientific and applied contributions of the dissertation research are:

NP1. Proposed architecture of a software system for managing the production process in a textile fiber factory;

NP2. Realized software prototype of a software system for managing the production process in a factory for the production of textile fibers.

Applied contributions of the dissertation research are:

P1. Implementation of the developed prototype of a software system in the company Suedwolle Group Italy – Bulsafil S.p.A.

P2. Conducted experiments to test the developed modules of the system;

P3. Experiments for automated report generation and notification were conducted.

The prospects for the development of the developed application are the construction of a centralized infrastructure with the ability to scale between different locations; integration of the developed system with IoT devices; integration of the developed software application with other systems, web and mobile applications; providing multilingual support and regulatory compliance; development of advanced analytics and AI modules; designing solutions for the needs of manufacturing processes in other industries.

The results of the dissertation research are presented in 4 publications, 2 of which are indexed in SCOPUS and have an impact rank:

1. **Trankov, M.**, E. Hadzhikolev (2021). Application of Machine Learning Methods in Planning the Production of Textile Fibers, at the Stage of Raw Material Preparation, Scientific Papers of the Union of Scientists in Bulgaria – Plovdiv. Series B. Technique and Technologies. Volume XIX,

2. **Trankov, M.** (2024). Automated Quality Management in the Production of Worsted Fibers, Scientific Papers of the Union of Scientists in Bulgaria – Plovdiv. Series B. Technics and Technologies. Vol. XXI,

3. **Trankov, M.,** E. Hadzhikolev, S. Hadzhikoleva (2024). Model of a system for forecasting the production of textile fibers. AIP Conference Proceedings, 2980 (1): 040001.

4. **Trankov, M.,** E. Hadzhikolev, S. Hadzhikoleva (2024). Machine Learning Algorithms in Quality Control of Textile Fiber Manufacturing. Journal of Theoretical and Applied Information Technology, 102(4), pp. 1673-1682.

1 citation of the publications on the dissertation was noticed:

The developed software system has been implemented in the company Suedwolle Group Italy – Bulsafil S.p.A. for planning the production of worsted yarns. The results obtained during the study have been used in 4 projects.

LITERATURE

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