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A Flexible and Intelligent Production System for Process Planning and Enterprise Performance Optimization

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Abstract. Many companies have been expending considerable efforts to continuously improve manufacturing processes to ensure their competitiveness and remain in the market. Value Stream Mapping is a strategic tool that makes it possible to visualize the macro of production to assist in planning and decision-making. It is a process mapping that considers the workflow of a product from the arrival of the raw material to the result that is delivered to the customer. Despite the benefits this tool has provided to organizations, the time for its development is still very high, as its data is still filled manually, allowing its analysis to be error-prone. Digital technologies have brought several improvements to the methods and tools of organizations. With the goal of obtaining contributions to engineering through transdisciplinary approaches to decision support tools and methods, therefore, this study will present the development of a dynamic web application using data analytics and machine learning to visualize, identify bottlenecks, predict, and update data in current and future state mappings. Intelligent systems tend to eliminate the routine activities of engineering, so this application will allow engineers and technicians to dedicate more time to dedicate themselves exclusively to activities that require a more challenging level of managerial decision-making.

Keywords. Production; Machine Learning; AI; Value Stream Mapping; Data Analytics

Introduction

Operations management is a crucial function for an organization's success, responsible for converting available resources into products and services that meet customer needs and expectations. The main objective of operations management is to ensure efficiency and effectiveness, optimize resource utilization, reduce costs, and improve product and service quality [1].

Technology has enabled a new transformation in production processes, leading to the emergence of Industry 4.0. Operations management is among the areas that have gained prominence in this new scenario. According to [2], among the unfilled

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development gaps related to process management and decision-making support, there is a search for the combination of traditional and effective methods and methodologies in the industry with digital technologies in order to obtain more excellent dynamics and agility in obtaining results, as well as increasing existing systems or methods with new features and functionalities. One commonly used methodology in organizations is Lean Manufacturing, an operations management approach to eliminate waste, reduce costs, and improve production process efficiency and quality [3].

Lean manufacturing can be highly effective when combined with digital technologies, allowing organizations to optimize their processes further and achieve a new level of efficiency and quality in production. Although each Lean technique's relevance is recognized, current research's primary focus is on Value Stream Mapping (VSM), an essential method for process optimization that aims to analyze, plan, and manage the flow of materials and information necessary to deliver a product to the customer [4].

Inadequate or ineffective decision-making can result in missed opportunities, performance decline, and bankruptcy. In addition, resources invested in these strategic decisions, such as time, money, and effort, can be wasted.

VSM is employed in creating the present and future states of the flow of information and materials in processes, with the primary objective of identifying, controlling, and improving activities that add or do not add value, which is related to the customer's evaluation of the value received [5].

Through the analysis of related works and the research gaps presented in the literature, it is clear that several studies associate the VSM with digitization, highlighting the potential that can be achieved with digital adaptations. However, there is a lack of application of a functional VSM in companies in the industrial production sector, both for the digital visualization of the VSM and for the development of a VSM with intelligent prognoses in predicting future state mapping.

Therefore, the main objective is to develop and apply a flexible, dynamic, and intelligent web application to create the current state mapping and predict the best alternatives and solutions for future state mapping in a case study in an agroindustrial equipment company in Curitiba.

The application of an intelligent system can be highly beneficial for manufacturing industries, allowing engineers not to spend time on routine activities and focus on more significant challenges. This application combines transdisciplinary knowledge, such as production engineering, computer science, data analysis, and AI.

The VSM application can complement systems such as ERP (Enterprise Resource Planning), MES (Manufacturing Execution System), and SCADA (Supervisory Control and Data Acquisition), widely used in the manufacturing industry. According to [6], ERP aims to manage resources and processes within an organization comprehensively, MES focuses on the real-time control and monitoring of manufacturing operations, and SCADA focuses on the control and automation of industrial processes. The VSM application can offer some advantages concerning the functionalities that may not be entirely performed by these other systems, such as the complete visualization of the value stream updated in real-time, direct integration with the database, identification of opportunities for continuous improvement and integration with predictions and ML (Machine Learning) algorithms for demand analysis and production planning.

Solving complex problems, according to [7], requires the contribution of other disciplines, including engineering, human interaction, business, and computer science, among others. The relevance of engineering and transdisciplinary science is vital for gains in quality and productivity in organizations. This study brings an application of a new development considering the potential benefits of transdisciplinarity since the collaboration between these disciplines is essential to develop an efficient and innovative web system that uses AI to improve the VSM, making it more flexible and capable of providing valuable insights for process improvement.

1. Methodology and Results

This research is classified as quantitative, applied, field research, bibliographic, and prescriptive. Prescriptive models aim to simplify solutions by guiding problem solvers toward the most efficient solutions possible. In this investigation, models are developed to examine and anticipate the behavior of variables[8].

1.1. Approach

The methodology of this project is based on DSR (Design Science Research), an approach aimed at solving problems. This methodology is carried out in five stages: problem identification and motivation, defining objectives for a solution, design and development, demonstration, and evaluation [9]. Thus, nine specific objectives were used related to each of these steps to fulfill the development of the application (Figure 1).

DSR Stages	Specific Objectives
1-Problem Identification and Motivation	Identifying the Aplication Context of the Solution in the Manufacturing Industry
2-Define the Objectives for a Solution	Investigating different Methods, Algorithms, and Platforms
3-Design and Development	Selecting a layered software architecture for the VSM application
	Structuring the specifications and requirements of the application
	Developing the back-end and front-end algorithms for Current State Mapping
	Developing the back-end and front-end algorithms for Future State Mapping
	Testing and debugging prediction functions for creating Future Mappings
4-Demonstration	Demonstrating the system application in a Manufacturing company through a proof of concept
5-Evaluation	Evaluating the system for its efficiency, reliability, and applicability

Figure 1. Correlation DSR Stages and Specific Objectives.

In the first stage, the application context for a manufacturing company solution was created, starting with a bibliometric analysis focused on searching for research demands related to the use of digital technologies with production planning and control [2].

In the second stage, many periodic meetings were held with the partner company to organize details of this development. Thus, the goal application was established for a web system for local access via a browser. In this stage, the primary investigations of which methods, algorithms, and platforms could be effectively used to achieve the desired result were also carried out.

The system was fully developed in the third stage on six virtualized applications through the container orchestrator tool Docker Compose. According to [10], Docker is an open-source platform that allows the automation of developing, deploying, and running applications inside containers. Containers are lightweight and portable units that store an application and all its dependencies, including libraries, configurations, or even the operating system, in a single package. One of the most vital points of using Docker compared to other platforms is its portability, allowing it to be reinstalled on different machines with all the same settings [11].

In structuring this methodology, the ETL (Extract, Transform, Load) process was used (Figure 2) to organize the importance and role of each application to achieve the complete project goal. The ETL process is essential because it helps improve the quality and consistency of data by organizing how information is cleaned, standardized, and processed before being stored [12].

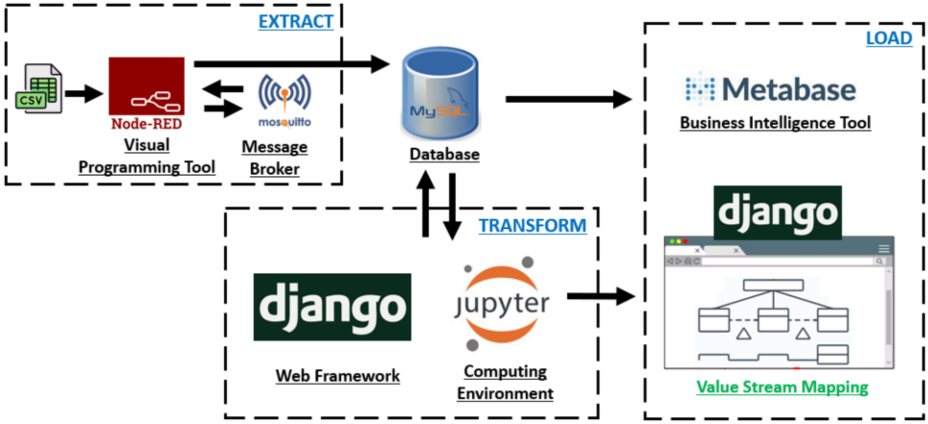

Figure 2. ETL for VSM Application Development.

Each application was installed on a single and isolated network within Docker so that they could communicate with each other.

Node-RED is an open-source visual programming tool that allows users to create applications and workflows by connecting "nodes" in a browser-based environment [13]. Mosquitto is a message server (message broker) that implements MQTT (Message Queuing Telemetry Transport) code and acts as a centralized intermediary to facilitate communication between applications [14]. Node-RED and Mosquitto were part of the "Extract" action and allowed data entry into the development environment to be operationalized.

The data collected are structured in an Excel file and later converted to the CSV (Comma Separated Values) extension, as this is the compatible extension for Node-RED.

From this, a flow of functions was created in Node-RED so that with just one click, it can read the CSV file saved in a directory on the computer and send this data to Mosquitto so that it can act as an intermediary to the flow of this information and ensure that it will be delivered correctly and in the same order as received. A second flow of functions was created in Node-RED to receive and read the data sent by Mosquitto and thus direct this information to the MySQL database creating a new table where all this information was available for access by any other applications in Docker.

The Django web framework, part of the “Transform” action, was used through the VSCode (Visual Studio Code) IDE, and all lines of programming for the current and future state mapping were developed. Python was used in the back end, while JS (JavaScript), CSS (Cascading Style Sheet), and HTML (Hyper Text Markup Language) were used for the front end.

In addition, as a complement to these mappings, it was possible to use the BI Metabase system, which is also on the same Docker network and has access to the same data in MySQL. Metabase can create a Dashboard of charts with complementary analyses to those performed by the web-based mapping. Jupyter Notebook, also integrated with Docker, is used as a real-time testing platform to analyze and validate the accuracy metrics of ML models used in future predictions.

In the fourth step, the system is applied and demonstrated in practice, mainly to validate the accuracy, flexibility, and innovation of the entire system. In the fifth and final stage, the system is evaluated using a questionnaire to assess consistency, usability, accuracy, reliability, performance, and flexibility.

1.2. Case Study

The partner company provided the latest mapping of a sequence of operations related to receiving, storing, transporting, and assembling fuel tanks, which they developed using traditional VSM resources. The process under study consists of 13 operations: Inbound Delivery, Typing, Unloading, Checking, Storing, Requesting, Order Picking, Loading (from Inventory), Transshipment, Kitting, Loading (from factory), Partial Assembly, and Assembly. The parameters used in each operation were: CO (Changeover Time) in minutes, CT (Cycle Time) in minutes, Availability in minutes, FPY (First Pass Yield) in units, Number of Operators in units, and WT (Waiting Time) in minutes. In addition, a timestamp variable was used to simulate the sequential observation of each operation and use this variable to order the mapping from the beginning correctly.

CO is the duration required to transition from producing one product to another, encompassing the adjustment of the production line configuration and preparation of materials. CT represents the overall time needed to complete a single production cycle, from initiation to completion. Availability denotes the ability of a machine, equipment, or resource to be present and functioning correctly during production, serving as a metric for the resource's readiness when required. FPY corresponds to the number of products that successfully pass an initial inspection or process without necessitating repairs or corrections, assessing the number of products produced accurately on the first attempt. WT occurs when an item or task awaits processing or inspection during production or operation.

Data prediction requires ML algorithms, which allow computers to learn from a certain amount of data, adjust their parameters and make predictions or decisions based on new data [15]. Since the amount of data provided was not considered sufficient, mainly for the development of future mappings, which need a considerable amount of data to make accurate predictions and thus obtain relevant results and insights, approximately 30,000 new lines of data were added using Excel software, all based on the data provided and keeping proximity of 3 numbers above or below the actual values.

1.3. Web Framework

In this application, five pages were developed: user sign-up, user login, Current State Mapping, Future State Mapping, and a page for a graphical comparison between the Current and Future State Mapping. Both pages have toggle buttons between them.

In the development of the Current State Mapping (Figure 3), there are several dynamic functionalities to facilitate usability in the analysis. The primary function of this page is to filter the table inserted in the database, and regardless of the number of existing rows, it only shows the last operations with different titles, as duplicate titles are not shown. Each operation is displayed individually with the five main production variables, except the Waiting Time variable, which is strategically placed in separate blocks between each operation block.

When accessing the current state mapping page, all blocks are automatically displayed, along with a bar graph created to complement the analysis of the variables of each operation. Initially, the chart displays the columns related to all variables for each operation, but it has the dynamic functionality of omitting any variables at each click on their respective names. In Figure 4, it is possible to see all omitted variables except the Cycle Time variable.

All the fundamental features and symbols of traditional VSM have been incorporated into this system but with user-friendly and easily applicable usability with just a few clicks. Using the right button on the mapping screen activates a modal selection of all VSM symbologies, such as process, material, and information symbols. Blocks can also be added for the information systems used in the process, creating connection lines from each operation to the information systems used and changing the colors of the connections for better differentiation between the links.

Figure 3. Current State Mapping.

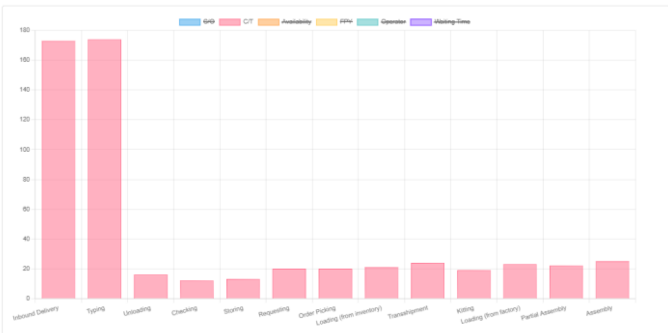

Figure 4. Cycle Time Bar Filtering.

On the future VSM screen, there are two data prediction simulators, the first one to simultaneously predict all five main variables of an operation (Figure 5) based on parameters of previous operations to it in the sequential order of the process, and the second simulator (Figure 6) to predict only one of the variables of an operation, inserting the other variables as parameters.

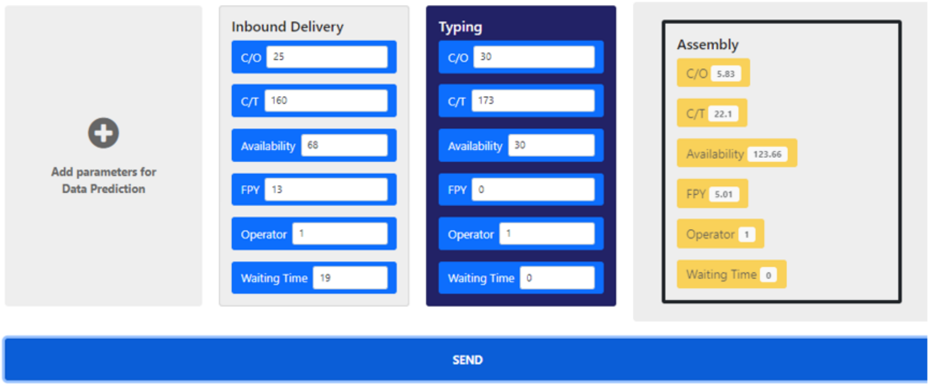

Figure 5. Operation Prediction Simulator.

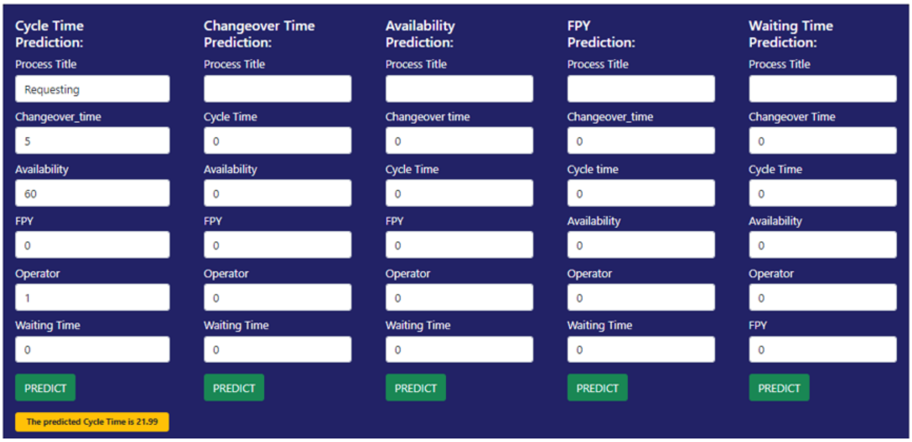

Figure 6. Parameter Prediction Simulator.

The user can choose any operation as the basis of parameters and enter data different from the data shown in the current mapping, choosing an operation that will be the target operation for prediction. Therefore, the simulator is flexible in organizing multiple possibilities of prediction analysis, for example, it will be possible to choose the first two operations to predict the behavior of the variables of the last operation or even use the first five operations to predict the behavior of improvement or worsening of the variables of the sixth operation. These simulations help engineers gain new insights based on existing trends in the database.

To determine the best ML models for these simulators, some tests were performed in Jupyter Notebook. Six ML models were analyzed using the metrics Cross-Validation, MAE (Mean Absolute Error), MSE (Mean Squared Error), R2 (R-Squared), and RMSE (Root Mean Squared Error). The models used were Random Forest Regressor, Kneighbors Regressor, Linear Regression, SVR (Support Vector Regression), MLP (Multilayer Perceptron) Regressor, and Gradient Boosting Regressor. Regarding the Parameter Simulator (predicting 1 variable) and the Operation Simulator (6 variables to simultaneously predict), the models that achieved the best results were the Gradient Boost Regressor and Linear Regression, respectively.

After the desired simulations, the user must insert the values to construct the future mapping (Figure 7). Once the two mappings are built, it is possible to visualize the two bar graphs together on another page, making it easy to analyze the variations between the process parameters.

Figure 7. Future State Mapping.

1.4. Validation

The system was demonstrated to the partner company's engineers in a practical demonstration. After completing the current state mapping, a comprehensive analysis was carried out to explore the future state mapping development with the prediction simulators through testing in four scenarios suggested by the partner company's engineers.

The first scenario involved predicting optimized parameters for the Unloading operation based on changes in the Inbound Delivery and Typing data. The second scenario focused on predicting parameters for the Storing operation, considering changes in the Inbound Delivery, Typing, Unloading, and Checking data. In the third scenario, parameters for the Loading (from inventory) operation were predicted based on changes in the Requesting and Order Picking data. Lastly, the fourth scenario aimed to predict parameters for the Assembly operation using changes in the Unloading, Loading (from inventory), and Loading (from factory) data.

It is important to emphasize that the data used in this project were not 100% actual but were used as a projection of trends, showing how each parameter variation influenced other values. The prediction simulator successfully generated positive and negative results between the resulting variables. Variations in the results were considered coherent with the reality of the operations after evaluation by the engineers. This confirmed that ML models could effectively predict various behaviors and consequences between parameter changes within a real-life scenario, reducing the need for time-consuming and resource-intensive hands-on checks if they had to be analyzed directly on the shop floor.

After the complete mapping, it was possible to create a dashboard in Metabase with four charts to demonstrate its features: (i) averages of all cycle time values and the averages of all FPY values; (ii) a count of repeated or similar cycle time values using the Pie visualization; (iii) averages of all changeover time values and the averages of all Availability values using the Area visualization; and (iv) maximum cycle time and minimum cycle time values using the Line visualization.

The feedback from the engineers, through the evaluation questionnaires, indicated satisfaction with the functionalities and dynamics provided by the VSM application. The system demonstrated viability for application in any production line, regardless of the amount of data, as long as each operation uses the same variables.

The results were of high quality, considering factors such as response time, resource consumption, number of errors, portability, and ease of use. The system exhibited relatively low response times for navigating different pages and performing tasks. In addition, its flexibility and scalability were satisfactory, as it efficiently processed the variables used without compromising machine performance. Finally, the system was praised for its user-friendly nature, employing intuitive mapping construction and a dynamic programming approach.

2. Conclusion

With the demonstration and evaluation stages, it is identified that the created solution achieved the proposed objective. The project was considered original as no development of VSM adaptation based on the web with traditional method functionalities combined with new dynamic and interactive functionalities and with ML algorithms for future predictions was identified in the literature.

Among the contributions of this project are the data feeding and organization strategy with the Node-RED, Mosquitto, MySQL, Django, and Metabase applications in an isolated network within a Docker virtualization environment, in addition to the development of a web tool that allows the creation, editing, comparison of results, prediction with the integration of ML algorithms, and assistance of the tool in the decision-making of organizations.

As a suggestion for future work, it is recommended to implement and test the system in other organizations and contexts, in addition to adapting this integrated system directly for cloud computing, as this will allow ease of access on other devices.

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