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Business Intelligence Using N-Beats And Rnn Methods End Influence On Decision Making In The Flexible Packaging Manufacturing

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Abstract – Today's complex decision-making solutions for intelligent manufacturing depend on the ability to be able to model a manufacturing system realistically, valid and consistent data integrated easily and in a timely manner, able to solve problems efficiently with computational effort to obtain optimal production and product quality optimizations continuously. When an organization uses a data-driven approach, it means that it makes strategic decisions based on data collection, analysis, and interpretations or insights. The purpose of this research is to analyze the business intelligence approach in optimizing print machines by speed, material and time. in this research, using the N-Beats is a deep neural architecture based on backward and forward residual links and a very deep stack of fully-connected layers and Recurrent Neural Networks (RNN). The novelty of this research is increasing machine speed using new insights by combining two deep learning methods. Observing and retrieving raw data from the printing machine process with sensors data for use and ensuring the justification of the addition of new methods. The result is expected to be able to provide new insights that can increase engine speed, the data based decision making provides businesses with the capabilities to generate real time insights and predictions to optimize their performance and provide confidence in decision making that are fast, precise and better.

Keywords – Business Intelligence, Recurrent Neural Networks, N-Beats, Decision-Making, Deep Learning, Insights

I. INTRODUCTION

To achieve genuine digital transformation, it is necessary to move beyond the asset-focused business intelligence approach and adopt a more holistic system that integrates Engineering, Operations, and Maintenance [1]. The increasing availability of data on volume, variety, and speed along with the increasing capabilities of computing and communications as well as the capabilities of modeling and solving complex analysis, is driving data into business using a combination of diverse and complementary types of process analysis [2]. The model possesses several desirable properties, including interpretability, adaptability to a wide range of target domains, and fast training. Two N-BEATS configurations, along with Recurrent Neural Network (RNN), were employed using the Python programming language. The problem that will be discussed in this research is how to optimize the printing machine production process using the N-Beats and RNN methods to analyze errors from the results of the model training process. To obtain the right parameters in an effort to speed optimized machine [3]. Focused on the three parameters generated by the machine sensor dataset, namely the type of material, speed and processing time and the process code for each machine unit [4].

The manufacturing industry is currently undergoing a paradigm shift due to the advancements in Big Data and Machine Learning (ML), which have now progressed to Deep Learning (DL) [5]. This transformation is moving the industry from the traditional manufacturing era to the intelligent manufacturing era 4.0, creating new opportunities. N-BETAS (Neural Basis Expansion Analysis for Interpretable Time Series Forecasting) [6]. The methodology for the architectural design of this system is based on a set of fundamental principles. Firstly, the architecture should be straightforward and versatile while still being comprehensive. Secondly, the architecture must not depend on feature engineering or input scaling that is specific to time series [7]. RNNs have been employed with success for various tasks that involve processing sequences of data such as sentiment analysis, machine translation, time-series forecasting, image captioning, and more [8].

II. RESEARCH METHODOLOGY

In the upcoming chapter, we will explain why quantitative methods were selected and how the empirical research was conducted. Then, we will outline the dataset retrieval design, which includes a brief introduction to the organizations involved in the thesis and the process of collecting the dataset from the machine. Finally, we will discuss the method analysis, the reliability of the research, and any criticisms of the chosen method.

A. Research Object

The purpose of this research is to improve the accuracy of forecasting predictions using the N-BEATS and RNN methods in computer models. The thesis focuses on these two models and aims to demonstrate their ability to generate new insights through prediction. The dataset utilized is comprised of engine sensor data in Txt format, which is stored in a SQL database. The data is then retrieved in CSV format, and the engine process data for the year 2021 is selected for use in the thesis. This section describes the proposed method for generating forecasting that can provide new insights by leveraging multiple parameters of sensor data. The model will process various parameters generated by the sensors to obtain effective forecasting predictions and extract insights from the data.

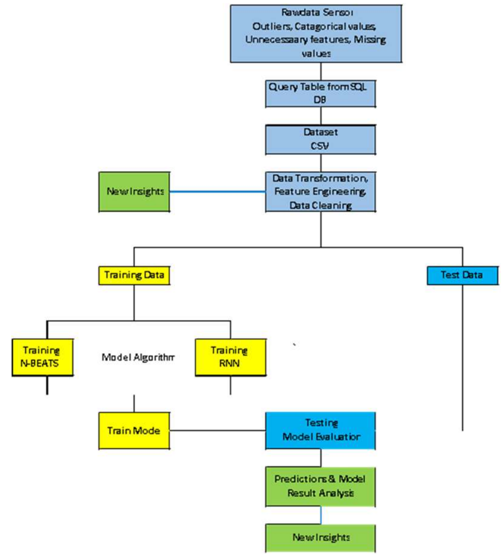

Figure 1 Flow Chart of Prosed Model and Implementation.

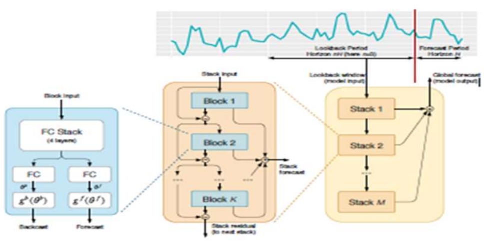

Figure 2 N-BEATS Architecture.

B. Predicting Forecasting by Machine

In this table, the "Model" column lists the names of the two models being compared. The other columns show the average values of different evaluation metrics for each model. The "RMSE" column shows the root mean squared error, the "MAE" column shows the mean absolute error, the "MSE" column shows the mean squared error, and the "SMAPE" column shows the symmetric mean absolute percentage error. In the Table 1, that shows the average results of the N-BEATS and RNN models for time series forecasting.

Table 1 Result of Predicting Forecasting by Material Types

Model	Types of Material	RMSE	MAE	MSE	SMAPE	AVG.
N-Beats	Material1	0,187	0,149	0,035	28,2%	20,0%
	Material2	0,242	0,182	0,059	81,7%	20,0%
	Material3	**0,233**	**0,188**	**0,054**	**84,6%**	**20,0%**
RNN	Material1	0,061	0,045	0,004	6,0%	10,0%
	Material2	**0,212**	**0,167**	**0,045**	**29,9%**	**20,0%**
	Material3	0,186	0,15	0,035	24,0%	20,0%

C. Prediction Accuracy Measures

The Root Mean Squared Error (RMSE) and the Mean Average Percentage Error (MAPE) are used to assess a models price predictions adequacy. These measures have also been used by many other studies.

$$MAPE = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{d_i - \hat{d}_i}{d_i}\right| \times 100 \quad (1)$$

III. Results And Discussion

The models used in this study achieved relatively good performance in terms of prediction accuracy. This means that the models developed are able to produce predictions that are close to the true value with a low error rate. In the study, the evaluation results showed that the models had good accuracy and were able to produce accurate predictions. With relatively good performance, the models can provide valuable insights and information in decision-making in the flexible packaging manufacturing industry. However, the N-BEATS model is superior in terms of prediction accuracy with lower mean values across all evaluation metrics. The results from both models provide valuable insights that can be used in optimizing press speeds in rotogravure printing processes. By identifying the optimal parameters based on the model predictions and increasing the output, companies can improve their productivity and process efficiency. In other words, the use of N-BEATS and RNN models in Business Intelligence analysis enables flexible packaging manufacturing companies to make informed decisions to improve the performance and effectiveness of their presses.

The use of Business Intelligence (BI) in the flexible packaging manufacturing industry has significant benefits [9]. With BI, companies can take better decisions based on accurate data analysis and easy-to-understand visualizations. This helps in understanding market trends, predicting product demand, and responding quickly. In addition, BI also enables cost reduction by identifying areas of waste and improving efficiency in the production process [10]. With product quality analysis, companies can improve quality and reduce defects through quick corrective actions. Finally, BI helps improve a company's competitiveness by providing deep insights into markets, customers, and competitive advantages [11]. Sbrana et al., (2020) This enables companies to take the right steps to meet customer needs and achieve an edge in the flexible packaging market.

1. Business Intelligence (BI) plays an important role in optimizing presses for speed by providing the insights and information needed to improve efficiency and productivity. Here are some of the ways BI can optimize presses based on speed:
2. Data Collection and Integration: BI involves collecting data from various sources such as press sensors, production logging systems, and other systems related to press speeds. This data is then integrated into a single BI system or platform for more holistic analysis.
3. Data Analytics: Through BI data analysis, patterns and trends related to press speeds can be identified. This analysis can involve statistical techniques, predictive modeling, and machine learning algorithms to unearth deep insights into the factors affecting press speeds.
4. Performance Monitoring: BI enables real-time monitoring of press performance. Actual speed data is collected and compared with set targets. If there is any deviation or drop in performance, BI provides notifications or reports that enable the operations team to take quick corrective actions.
5. Process Optimization: Using insights from BI,

companies are able to identify the causes of printing press speed non-optimization. This allows them to optimize the production process by making necessary operational improvements or adjustments. For example, BI can help in identifying bottlenecks, organizing an efficient task sequence, or adjusting machine settings.

6. Planning and Decision Making: BI also helps in long-term planning by providing the information needed for strategic decision-making related to investments in new equipment, preventive maintenance, or changes to more efficient production processes. With a better understanding of press speeds and the factors that affect them, companies can make smarter decisions to improve performance and productivity.

Through the application of BI in press management, companies can gain better visibility, identify opportunities for speed improvements, and take the necessary actions to optimize production processes. Thus, BI can help companies achieve higher efficiency, reduce production costs, increase output speed, and bring significant added value [13].

Business Intelligence (BI) plays an important role in optimizing material-based molding machines by providing the information and insights needed to improve production efficiency and quality [14]. Zeng et al., (2021) here are some of the ways BI can optimize presses by material:

1. Material Availability Analysis: Using BI data, companies can analyze the availability of materials required for the print process. This data includes material inventory, delivery time, and supplier capabilities. By looking at the data, companies can predict future material demand and optimize inventory so that the production process is not interrupted by material shortages [16].
2. Material Inventory Management: Using BI analysis, companies can optimize material inventory arrangements. For example, by looking at historical demand data and market trends, companies can determine the optimal inventory levels for each type of material [17]. This helps avoid wastage and excessive storage costs, while ensuring materials are available on time for production.
3. Material Quality Monitoring: BI can help in monitoring the quality of materials used in the molding process. Quality data and indicators can be collected and analyzed in real-time to detect any discrepancies or defects in the materials. Thus, companies can take immediate corrective actions, reduce the risk of defects in molded products, and increase customer satisfaction.
4. Material Efficiency Analysis: BI can help companies identify factors that affect material utilization efficiency. Data collected from molding machines and other production systems can be analyzed to identify possible waste, material loss, or imperfections in the production process. By understanding the patterns and causes of material wastage, companies can take action to optimize material usage and improve production efficiency [18].
5. Planning and Decision Making: Using BI, companies can make better plans related to material procurement, supplier selection, and inventory management. BI data and analysis help in making strategic decisions related to materials, such as evaluating new suppliers, looking for more efficient material alternatives, or adjusting material procurement strategies based on market trends.

Business Intelligence (BI) can help optimize presses based on time by providing deep insights into press performance, real-time monitoring, and historical data analysis. Bulatov, (2020) here are some of the ways BI can be used to optimize presses over time:

1. Molding Machine Performance Monitoring: BI enables companies to monitor press performance in real-time. Operational data such as print speed, downtime, and reset time can be collected and analyzed in real time. This helps in identifying possible performance issues, such as unplanned downtime or low print speed. With proper monitoring, companies can take quick corrective actions and optimize the uptime of the press.
2. Downtime Analysis: Downtime is the time during which a press is not operating. Using BI analysis, companies can identify the causes and duration of downtime, both planned and unplanned [4]. This data can help in optimizing routine maintenance schedules and minimizing unnecessary downtime. In addition, downtime analysis also helps companies identify contributing factors and take preventive actions to reduce downtime in the future.
3. Demand Prediction: Through the analysis of historical data and market trends, BI can help companies predict future demand for printed products. This information allows companies to conduct [20] better production planning, optimize production schedules, and avoid situations where presses experience idle time or overload. By predicting demand with greater accuracy, companies can optimize the use of printing presses and avoid wasting resources.
4. Production Efficiency Analysis: BI allows companies to analyze production efficiency based on time. Operational data and production parameters such as cycle time, preparation time, and reset time can be analyzed to identify areas where efficiency can be improved. For example, companies can evaluate the optimal cycle time for each printed product or identify activities that take too long in the production process. With this analysis, companies can optimize the use of time and increase the productivity of the printing press.
5. Production Planning and Scheduling: BI helps in efficient production planning and scheduling. By collecting and analyzing time-related data, BI enables companies to create better production schedules based on press capacity, product demand, and resource availability [21]. This helps

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avoid production time imbalances that can result in machine overutilization or underutilization.

IV. CONCLUSION

Both models achieved relatively good performance in terms of prediction accuracy. The N-BEATS model outperformed the RNN model in terms of prediction accuracy, with lower average values across all evaluation metrics. The insights gained from these models can be used to optimize machine speed in the rotogravure printing process. By identifying the optimal parameters and increasing the output, the productivity and efficiency of the process can be improved. For future work fine-tune hyperparameters such as learning rate, batch size, number of layers, and number of neurons can significantly affect the performance of the models. Future work can explore different hyperparameters to find the best combination for the given dataset.

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