Integrated Master Production Planning and Machine Learning-Based Failure Prediction Using Event-Based Time Series Data with Mathematical Modeling

Hamid Mohammadi [1,*] - Hossein Karimi [2]
[1] Department of Industrial Engineering, Shahed University, Tehran, Iran
[2] Department of Industrial Engineering, University of Bojnord, Bojnord, Iran

ABSTRACT

This paper deals with the problem of integrated predictive maintenance (PdM) and master production planning (MPP) in a real multi-machine packaging system. In contrast to prior work in which environmental variables of machines and components or popular datasets were used, we employed event-based historical data of machine failures. Four machine learning (ML) models for failure prediction were built with the Deep Neural Network (DNN) outperforms the other. We proposed a dynamic linear programming (DLP) model to determine optimal production strategies while minimizing costs. While previous studies concentrate mainly on scheduling and planning, our research concentrates on the higher master production level. The framework was tested using real-world data from a one-year data collection, and analyses of three scenarios revealed different trade-offs between production strategies. This study provides practical evaluation in the area of maintenance for professionals using failure prediction analysis. Moreover, the approach proposed in this framework can help planners to decide which strategy they would like to implement based on the key production and cost-related parameters specific to their business. In conclusion, this paper as a strong methodology provides managerial insights for decision-makers and highlights future directions to advance the adaptability of manufacturing processes in the Industry 4.0 environment.

Keywords: **Master production planning, Predictive maintenance, Machine learning, Failure prediction, Deep neural networks, Optimization**

1. *INTRODUCTION*

In today's Fourth Industrial Revolution context, integration of impact factors that affect productivity and cost of the supply chain is crucial. Machine failure and production planning as the basic components have been developed in various technological models and research fields. When an unplanned downtime, caused by a production line failure occurs, it often trims down the system's productivity and renders the current production plan obsolete. Therefore, Maintenance planning should be an integral part of the overall business strategy and should be coordinated and scheduled with manufacturing activities [1]. This results in fostering operational efficiency, assets durability, downtime minimization and finally overall productivity. It leaves no doubt that both these two activities are correlated and both are holding an important position in increasing the profit margin and the effectiveness of the company. It is worth mentioning that because they use same resources, there are also in conflict with each other, but the synchronization between the production planning and preventive maintenance (PM) activities may avoid failure, production delays and replanning problems [2].

In the literature, there are four main maintenance strategies; Reactive Maintenance (RM), Scheduled Maintenance (SM), Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM). RM occurs when a machine component is failed and can no longer operate. This strategy is risky from the point of view of safety measures and higher costs to restore the catastrophic failures, and a higher amount of time to be repaired [3]. SM is a strategy where maintenance is carried out at pre-decided time intervals. It comprises inspections, adjustments, and planned shutdowns. The SM strategy's primary goals are to reduce the cost of reactive maintenance and machine failures. The repair cost, however, is generally less in SM compared to RM. Condition-based maintenance involves continuously monitoring and replacing an asset when it stops functioning normally [3]. In this research, we integrated master production planning (MPP) with failure prediction, specifically predictive maintenance (PdM). Using historical event-based machine failure data enabled us to predict when failures will occur and when maintenance is needed. This strategy supports lean manufacturing [4]. By analyzing historical failure data, this strategy predicts maintenance requirements, reduces maintenance expenses and therefore improves overall operational efficiency and durability of machines through correct utilization of resources. This gives the production scheduling experts information on the maintenance schedules thereby allowing plans to be put in practice on the machines at appropriate times. This reduces occurrence of interruptions to the production process, the likelihood of unexpected downtimes in future, and enables better control on capacity losses. Moreover, this approach is helpful in making more accurate and realistic decisions. Overall, MPP integrated with machine failures would increase production line efficiency, optimize resource consumptions, and lead to high customer satisfaction.

1.1 Industry application

Research on failure prediction and production integration has highlighted applications in industries such as aircraft, data center, oil & gas, automotive and manufacturing industries. Dangut et al. [5] suggested a Machine Learning (ML) approach to predict extremely rare aircraft component failure. A roadmap for maintenance planning extracted from sensor measurements using Remaining Useful Life (RUL) prognostics was proposed by Lee & Mitici [6] to limit the wasted life of aircraft turbofan engines. Gour & Waoo [7] introduced tree-based algorithms for classifying and forecasting the likelihood of hard drive failures in the data center. Surveys such as that conducted by Arena et al. [8] have analyzed the historical data on maintenance alerts of the components of a revamping topping plant belonging to an industrial group in oil & gas industry. Zhai et al. [9] assessed the applicability of their operation-specific health prognostics approach in a real industrial use case, a proprietary dataset of multifunctional machining centers for automotive component manufacturing. Hulbert et al [10] presented a method to predict impending vehicle system faults by analyzing sensor data in the automotive industry for improving diagnostics and preventing errors. But, a large body of literature has investigated integrated predictive maintenance and production planning focused on the manufacturing sector to reduce costs and downtime. Seminal studies in this area were the works of Cassady & Kutanoglu [11], Sortrakul et al. [12], Aghezzaf et al. [13], Najid et al. [1] and Fitouhi & Nourelfath [2] that simultaneously determined production scheduling and preventive maintenance planning decisions for small size problems and attempted to show effectiveness of proposed integrated models. Vast majority of recent research into the integration of production and maintenance activities in the manufacturing sector such as Sobaszek et al. [14], Zonta et al. [15], Leukel et al [16], Sengottaiyan et al [17], Nasser & Al-khazraji [18], Shoorkand et al [19], Tortora et al. [20], Pinciroli et al. [21] and Shoorkand et al [22] has focused on data-driven approach being solved by ML algorithms that can be categorized as new generation of studies.

1.2 Model-based Approach

A significant body of research on integrated models utilized model-based methodologies. Cassady & Kutanoglu [11] and Aghezzaf et al. [13] and Aghezzaf & Najid [23] developed a mathematical model for integrated production scheduling and PM planning problem. The problem of determining optimal integrated production plan and date of preventive maintenance in a multi items capacitated lot sizing problem with demand shortage was formulated by Najid et al. [1]. Similarly, Fitouhi & Nourelfath [2] proposed a model determines simultaneously the optimal production plan and the instants of non-cyclical preventive maintenance actions under demand fluctuation for a single machine. Alimian et al. [24] presented a robust integrated mathematical model for production and preventive maintenance planning in multi-state systems, considering uncertain demand and common cause failures.

1.3 Machine Learning Approach

In recent years, there has been an increasing amount of literature on using ML techniques for predictive maintenance. It is a powerful tool for failure prediction [20]. ML algorithms enable the development of models from existing data to create models that can forecast new data outcomes. ML approaches, classified into unsupervised, semi-supervised, supervised, and reinforcement learning, have been applied in several tasks related to maintenance, such as failure detection, failure diagnosis, condition monitoring, remaining useful life, and failure prediction [20]. In [8], three ML algorithms: Linear regression, ARIMA and Regressor Based on Polynomial Integration were applied to provide strategic support for the definition of an adequate maintenance plan through using simple natural language processing techniques and performing a clustering. Smart sensors data have been pre-processed in [24] to serve the evaluation of four regression ML models; Bayesian Linear Regression, Poisson Regression, Neural Network Regression, and Random Forest. In [26], an adaptive ARIMA ML model was proposed to support adaptive error prediction through a varying windowing technique. Therefore, future breakdown before its occurrence by forecasting the important signature parameters in the machinery can be predicted. Wang et al. [27] used a Bayesian algorithm for online RUL prediction of rotating machinery components in real time. The authors in [1], [19] and [28], collected real-world data for training and testing a Long Short-Term Memory algorithm to estimate the remaining useful life of the monitored equipment. The study in [20] used two ML methods, Random Forest (RF) and Decision Tree (DT), to predict the failure based on binary classification with a cost-oriented approach.

1.4 Data source

Industry 4.0 is based on utilizing nine technologies, including simulation, industrial internet, vertical and horizontal system integration, cybersecurity, cloud computing, big data and analytics, augmented reality, advanced robotics, and additive manufacturing. Furthermore, IT systems, workpieces, machines, and sensors are all linked with a value chain that goes above a single company [4]. Such interlinked systems can allow for interaction and assess the data for predicting the operational performance levels of an enterprise [4]. For instance, a company can plan and do predictive maintenance at the most proper time using big data and ML techniques. In recent years, widespread use of data-driven approaches is seen for predicting machine breakdowns, identifying the main causes, and recommending the most effective actions to increase performance. These methods improve accuracy, and enhance decision-making leading to greater operational efficiency and cost savings. In the literature, this is done by considering possible environmental variables (for instance, torque, strength, temperature, vibration, pressure, lubrication levels, etc.) or utilizing well-known datasets including those that could trigger a failure. In reference [14], the historical failure times including the data on the history of maintenance and repair of technological machines were used. Condition-monitored data (temperature, vibration and pressure) for the plant’s critical equipment components namely electric motor, gear and blower of a single-stage centrifugal compressor, were collected in [29]. Singh et al. [30] employed a failure dataset from the National Aeronautics and Space Agency (NASA) to forecast potential faults of rolling element bearings. Dangut et al. [5] used real log-based aircraft central maintenance system data, which is not often used for predictive maintenance modelling. The frameworks in [7], [9], [20], and [25] are validated on the well-known public dataset of Backblaze, the C-MAPSS FD002 dataset, the time-series dataset of Azure blob storage and Microsoft Azure ML platform respectively. A benchmarking subset data, FD001, developed by NASA was used in [19] and [22] that contains a training and testing set which consists of 26 columns, including the unit numbers (Id), cycle numbers, three operational parameters, and 21 data of various sensors. In [8], the data of historical maintenance alerts consist of “Notices” and “ODM” (maintenance orders) where the features of interest for analysis are the identification number of the notice, description, date of the event, technical office and the name of equipment. In [16], Operational data of fourteen components of the milling machine for about 25 months were available, and all observations were recorded with a frequency of 30 seconds. The time-series data in [18] comprised historical data on telemetry, machines, errors, and failures, representing various events from 100 different machines on an hourly basis over a one-year period. Lee & Mitici [6] used the degradation data of aircraft turbofan engines obtained by NASA, which consists of data subsets considering a specific number of fault modes and operating conditions. In reference [28], Sensor values that monitor different parameters of a production machine collected every five milliseconds were stored in a local database in the motion controller and then transferred to a PLC database and finally data values were stored in the historical database. Authors in [15] used Microsoft Azure AI-based PdM dataset providing telemetry readings taken every hour on voltage, rotation, pressure, and vibration sensors for several machines. Microsoft's real-world example is the source of the data utilized in [17] where machine characteristics and telemetric, such as power, temperature and rotational sensor readings, are also included in the collection for a total of 100 workstations through a whole year gathered hourly for every device. The subject of [31] is a DJI M600 multirotor Unmanned Aircraft System, which has 6 rotors with two blades each and it is controlled by a DJI N3 autopilot in a closed laboratory environment. Its main sensor contains an accelerometer, a gyroscope and a magnetometer and is able to capture data from all axis.

In the proposed system of [26], the value of oil contamination is measured using the sensor deployed in the hydraulic unit of a grey casting foundry on a molding line, once in every 3 minutes of interval through a wireless sensor network. The oil contamination sensor measures the oil contamination level in mA, which is proportional to the oil contamination level of the NAS 1638 standard. The dataset in [21] contains records from sensors installed on different components of a wrapping machine, a blood refrigerator and a nitrogen generator. The dataset includes information from IoT sensors that measure various variables such as temperatures, motor frequencies, platform speeds, energy consumption and the nitrogen and CMS air pressure.

1.5 Key Findings

Initial studies in integrated predictive maintenance and production planning literature emphasize the effectiveness of the proposed models such as the works of [1], [2], [11] and [13]. Most researchers have highlighted the effectiveness of their solution approach. In [12], the proposed genetic algorithm was introduced as an effective method to solve the integrated problem. Reference [21] demonstrates effectiveness of DL approaches in classifying data with diverse time-dependent patterns preceding a failure. The evaluation results show the effectiveness of the proposed hybrid CNN-LSTM model for PdM problem in [17], [18] and [22] due to its higher prediction accuracy. Key contributions in [9] and [15] are utilizing efficient deep learning approach to accurately predict machine failures, thereby enabling predictive maintenance planning. In [25], Random Forest outperformed other ML algorithms with an average R^2 of 0.96 as the most exciting finding. Redundant and preventive stoppages in the production line were reduced in [28] at the same time, decreasing the cost of maintenance operations based on LSTM-autoencoders. As another distinctive contribution, a comprehensive decision support system was presented for a complex cyber-physical production system in [32], which enables mapping the entire complexity of real-world production systems and supports production and maintenance planners in the multi-criteria decision-making process. Two novel studies, [5] and [8], employed natural language processing techniques to categorize faults and create structured data to enhance the prediction accuracy by ML applications. The proposed process in [20] differs from pre-existing ones due to a cost-oriented approach through which ML algorithm for failure prediction is chosen to minimize maintenance costs through a cost-based selection phase. In reference [31], a new method, called mean peak frequency, was proposed to estimate RUL using vibration data collected from a multi-rotor UAS to assess degradation. The main finding in [16] was understanding of how sliding window selection can effectively be used for ML-based failure prediction. The study in [29] found that the components with the shortest life expectancy require more frequent monitoring and maintenance, besides the fact that operating speed and functionality significantly affect the deterioration rates of all components. [14] focuses on utilizing historical data and effective prediction algorithms to forecast machine failures, integrating TBM principles with probabilistic approaches to enhance the reliability and efficiency of multi-machine manufacturing systems. Development of a framework that achieves dynamic decision-making and cost minimization through the integration of deep learning with mathematical programming is considered to be the main success in reference [19]. The research in [7] differentiates itself by integrating ensemble learning with deep neural networks to improve the accuracy of failure predictions, especially in handling imbalanced data. New avenues are opened in [6], applying probabilistic RUL prognostics to optimize maintenance decisions through formulating the RUL estimation as a Markov decision process (MDP).

Motivated by the advantages of integrating failure prediction and production planning, the present study aims to develop a framework to determine the optimal master production decisions and the anticipated maintenance activities under certain demands in a real multi-machine manufacturing system of packaging household polymer products. There are several important areas where this study makes an original contribution. The importance of this study is that according to real event-based historical time-series failure data collected over the course of a year, categorized into machine specifications, failure information, time-related data and the health condition of the production machines for PdM purposes has been predicted. Finally, the optimal production planning strategy is established for the entire planning horizon. This paper is organized into 6 sections. The remaining part of the paper proceeds as follows. Section 2 describes the problem, presents the integrated framework and overview of the used ML algorithms. Additionally, the dynamic mathematical modeling for the problem is presented. Section 3 illustrates using historical data to validate our ML algorithms. Section 4 discusses the results of a numerical example for the scenarios, where the proposed framework is employed to predict the failure, and the optimization model is implemented to determine optimal values of decision variables across the planning horizon. In section 5, we attempt to present the main objectives of this research, which are applicable in industries, especially in the field of decision-making. The conclusions along with future research directions are summarized in Section 6.

2. *PROPOSED INTEGRATED FRAMEWORK*

In this study, a plant produces a variety of plastic-based household and commercial products using a multi-machine packaging system. ML models predict machine failures in the planning horizon. And a linear programming model optimizes production while managing machine failures to minimize costs. In this integrated model, the aim is to predict failure, improve maintenance engineering, and balance in-house and outsourced production values considering probable delayed orders and capacity extensions.

In contrast to popular ML algorithms that learn the health patterns of machines to predict the RUL according to collected data by sensors, we used historical event-based time-series failure data of machines to predict our binary target variable, will fail soon (WFS), in the next planning periods. The WFS threshold is set to 60 minutes, meaning the target variable is set to 1, indicating a failure soon, if downtime exceeds 60 minutes. Otherwise, it is set to 0. Setting a threshold for the WFS highlights the focus of the proposed framework on preventing and managing the most disruptive and critical downtime events, which are most relevant to operational efficiency and resource management. Longer downtimes might point toward significant problems or critical failures in the machinery which need more time, technical priority and attention to solve, so predicting and avoiding them is more crucial than responding to every minor issue. Predicting WFS with high performance plays a critical role in reducing the overall downtime and optimizing maintenance schedules. To uncover hidden patterns, predict accurately, and make more efficient and timely maintenance decisions, we used ML techniques in line with the literature.

Our ML algorithms take time-series data as inputs to extract the representations of the machine's health condition. Given that our data have been collected with a great level of detail by the maintenance department, the desired output in the first step (failure prediction) is the day and duration of failure, categorized by the machine coding and type of failure in the system and its components. In other words, in the first stage, as seen in Table 1, we aim to determine which machine and components will fail on what date, for how many minutes, and due to what reason.

In the second stage, (master planning), based on the predicted downtime obtained for the machines in the first step, the actual remaining usable capacity of the machines has been calculated. This means that the proportion of time lost to total available machine time has been computed and then subtracted from the total capacity. For instance, this deterioration in the model is presented as a reduction of production lines capacities in function of the time evolution in [33]. According to this capacity and the demand for each product within the planning horizon, we determined the number of products that could be produced in-house, outsourced, backordered or produced with extended capacity through our LP model.

2.1 Plant Description

The Zarin plant is one of the manufacturing units in Tehran, Iran, where the main product groups produced include Sheet Freezer Bag, Freezer Bag Roll, Dispenser Box Freezer Bag, Garbage Bag Roll, Easy Tie Garbage Bag, Plastic Disposable Tablecloth and Disposable Glove. The main goal in the sewing hall is to manufacture convenience items designed for household and commercial use from semi-finished products that have come from the previous hall, production hall. These semi-finished products are typically made from various types of plastic materials. In the sewing multi-machine system, different advanced packaging machines equipped with servo drive motors and PLC systems perform perforating, sewing, and cutting operations with high efficiency according to the dimensions of the desired products. These semi-automatic machines efficiently process materials across multiple lines, handle various roll widths, and produce high volumes of final products per hour. Automation including pneumatic jacks and inverter controls ensures precise, high-speed production with minimal manual intervention. The functioning of the machines consists of cycles with irregular lengths, depending on the size, weight, dimensions and thickness of the products. A cycle consists of five steps:

1. Loading the semi-finished rolls onto the machine's opener
2. Guiding the film towards the sewing and cutting section

3. Sewing the film along the specified lines and at the same time cutting or perforating to the required size with a cutting or perforating blade
4. Counting and collecting the finished bags after a specified number
5. Batching and packaging the finished product for easy separation by the operator

Table 1. *Failure prediction of 5th month*

Date	Machine Coding	System-Wide Failure	Component Failure	Start Time	Finish Time	Failure (mins)	Shift
29/05/2023	SCA101	Mechanical	Perforating Blade Failure	[Timestamp('2023-05-29 22:00:00')]	[Timestamp('2023-05-29 12:00:00')]	600	Night
09/05/2023	SCA106	Mechanical	Settings Failure	[Timestamp('2023-05-09 15:00:00')]	[Timestamp('2023-05-09 17:30:00')]	150	Day
11/05/2023	SCA108	Mechanical	Collector Plug Failure	[Timestamp('2023-05-11 20:00:00')]	[Timestamp('2023-05-11 08:00:00')]	720	Night
21/05/2023	SCA108	Mechanical	Settings Failure	[Timestamp('2023-05-21 09:00:00')]	[Timestamp('2023-05-21 11:00:00')]	120	Day
27/05/2023	SCA108	Mechanical	Fireproof Failure	[Timestamp('2023-05-27 20:00:00')]	[Timestamp('2023-05-27 21:30:00')]	90	Night
13/05/2023	SCA201	Mechanical	Settings Failure	[Timestamp('2023-05-13 08:00:00')]	[Timestamp('2023-05-13 09:40:00')]	100	Day
24/05/2023	SCA201	Mechanical	Plastic Roller Failure	[Timestamp('2023-05-24 08:00:00')]	[Timestamp('2023-05-24 17:00:00')]	540	Day
31/05/2023	SCA201	Mechanical	Plastic Roller Failure	[Timestamp('2023-05-31 08:00:00')]	[Timestamp('2023-05-31 10:00:00')]	120	Day
20/05/2023	SCA202	Electrical	SSR Failure	[Timestamp('2023-05-20 08:00:00')]	[Timestamp('2023-05-20 10:00:00')]	120	Day
21/05/2023	SCA202	Mechanical	Glue Failure	[Timestamp('2023-05-21 08:00:00')]	[Timestamp('2023-05-21 12:00:00')]	240	Day
11/05/2023	SCA301	Electrical	Fault in Electrical Panel	[Timestamp('2023-05-11 08:00:00')]	[Timestamp('2023-05-11 14:00:00')]	480	Day
22/05/2023	SCA301	Mechanical	Metal Roller Failure	[Timestamp('2023-05-22 09:00:00')]	[Timestamp('2023-05-22 14:00:00')]	420	Day
06/05/2023	SCA302	Mechanical	Blade Failure	[Timestamp('2023-05-06 10:00:00')]	[Timestamp('2023-05-06 14:00:00')]	240	Day
27/05/2023	SCA303	Mechanical	Settings Failure	[Timestamp('2023-05-27 08:30:00')]	[Timestamp('2023-05-27 10:00:00')]	90	Day
27/05/2023	SCA304	Mechanical	Cutting Blade Failure	[Timestamp('2023-05-27 21:30:00')]	[Timestamp('2023-05-27 23:00:00')]	90	Night
31/05/2023	SCA305	Mechanical	Cutting Blade Failure	[Timestamp('2023-05-31 08:00:00')]	[Timestamp('2023-05-31 23:40:00')]	940	Day

2.2 Assumptions

The following assumptions are taken into account.

a. The manufacturing system consists of several parallel machines, each group of which is capable of producing a specific group of products.
b. Maintenance actions restore the machine to an ‘as-good-as new state’.
c. Repair should be carried out as soon as the failure occurs and the factory's technical personnel possess adequate knowledge for fixing any type of repair.
d. The spare parts for machine components that need replacement are available in the spare parts warehouse.
e. The planning time horizon initially begins with a new or as good as new machine.
f. The demand for products in each planning period might exceed the factory's production capacity.

g. Each machine has the ability to process a specific group of products, and the nominal capacity of the machines is the same in each planning period
h. Part of the demand that cannot be met in the current period will be fulfilled through outsourcing, but outsourcing capacity is limited for each product in each planning period.
i. Any unmet demand beyond both in-house and outsourcing capacity will be placed on backorder and fulfilled in the following periods, when capacity becomes available.
j. There is a lead time for backorders, meaning they cannot be fulfilled immediately in the next period, but only not later than a certain number of months.
k. Backorders incur increasing penalties the longer they remain unfulfilled.
l. The longer a backorder remains unfulfilled, the higher the penalty. This penalty increases over time to reflect customer dissatisfaction due to delayed deliveries. The penalty multiplier is set 1.2 in the model which means that if a backorder is not fulfilled in the specified lead time, the penalty cost will increase by 20% over the base backorder cost.
m. There are no backorders carried over from months prior to the start of the planning horizon.
n. There is also an opportunity to extend the in-house production capacity by adding additional machines. This capacity is purchased at a per unit cost and increases the amount of capacity available in other periods in the future.
o. Capacity extensions are dynamic and can be added at any month. When the extension is made, the increased capacity is available for all future periods.
p. Backorders older than 2 months that cannot be completed by in-house production or outsourcing must be finished through capacity extension.
q. Capacity loss is resulted from those machine failures that exceed the WFS threshold.

2.3 Problem description

In the assumed multi-machine production system, the machines are subject to random failures. When an unexpected machine failure happens, a maintenance action is performed, meaning the machine is returned to working condition without affecting its operational age. Alternatively, if necessary, the pneumatic, electrical, or mechanical components should be replaced. Let us consider a set of machines m ϵ {1,2, …, M} that are responsible for sewing a set of group products p ϵ {1, 2, …, P} over a defined finite planning horizon T with t planning periods, t = {1, 2, …, T}. Each period has the same fixed length L. The capacity of machines during each planning period is the same. Parameters may vary based on production characteristic and planning tactics of the that specific business. For instance, in the numerical example, we set T=12. A pre-defined demand for product p in month t, $d_{p,t}$, should be met and any unmet demand in each planning period must be produced through outsourcing. If both in-house and outsourcing capacities are insufficient, the unmet demand will be placed on backorder and fulfilled in the following periods when capacity becomes available There is a lead time for fulfilling backorders. Backorders incur penalties that increase as the demand remains unfulfilled for a longer period.

If the available in-house and outsourcing capacities are inadequate, the factory can increase in-house capacity by adding new machines that would boost the factory's production capacity in later time periods. Thus, the capacity and then flexibility can be increased to meet the upper future demand or to reduce backorders.

2.4 ML Algorithms

Different ML techniques are used to predict the machine health state that is stated in a binary-state. The proposed approach presents a data-based failure prediction model for a production system that can be incorporated into master planning. By collecting real historical data from the past year's machine failures in the designed format, the proposed framework helped to calculate the remaining in-house production capacity for product groups in each month, r_(p,t). Four ML approaches including deep neural network (DNN), Logistic Regression (LR), Support Vector Machine (SVM) and CatBoost (CB) are used to predict timing and type of failures in each planning periods.

2.4.1 *SVM Model*

SVM is a common supervised ML algorithm that is used for classification and regression analysis. The goal in this algorithm is to find a hyperplane that separates data points of different classes in a high-dimensional space. In other words, SVM attempts to find the optimal decision boundary that maximizes the margin, or the distance between the decision boundary and the nearest data points of each class. To accomplish this, SVM maps the data into a higher-dimensional feature space where it becomes easier to find a hyperplane that can separate the data [4]. Pinciroli et al. [21] predicted system failures utilizing six algorithms including support vector machine where results were also compared on multivariate time series. In reference [21], the impacts of different reading and prediction windows were tested for SVM, considering accuracy, precision, recall, and F1-score metrics.

In this implementation, SVM is employed particularly to predict potential failures to minimize unplanned downtime. After preprocessing the data and feature engineering, we applied PCA to reduce dimensionality while retaining the majority of the variance, preventing overfitting. In order to ensure optimal performance, we tuned the hyperparameters using GridSearch with cross-validation. After training and evaluation with regular performance metrics, it is used to predict machine failures over specific months, allowing for early intervention and maintenance planning.

2.4.2 *Logistic Regression (LR) Model*

The LR model is a common mathematical model in ML, and it belongs to probability type regression to describe and infer the relationship between multi-class dependent variables and a set of explanatory variables. The logistic function of the LR is Sigmoid function, which constrains the logistic probability of an event occurrence between 0 and 1 [19]. Experimental results in [21] demonstrate that basic, general-purpose algorithms, such as logistic regression, already achieve acceptable performances on complex datasets, where complexity is the mean of spectral entropies. Feng et al. [34] presented RUL estimation of aircraft engine by the combination of AEKFOS-ELM and logistic regression (LR) model and assessed its effectiveness on NASA engine degradation datasets.

In this study, to boost the model's performance, hyperparameter tuning is conducted using GridSearch, focusing on optimizing the regularization strength and solver selection for the logistic regression model. The best model, selected through cross-validation, is assessed using various performance metrics, which makes the evaluation more reliable. The final model is applied for a specific number of months to predict failures and plan maintenance thus determining the particular machines most prone to fail and which months are likely to have failures.

2.4.3 *Deep Neural Network (DNN) Model*

Neural networks and their subdivisions have been a major area of interest within the field of integrating predictive maintenance and production planning. For all models, dense layers were used with Softmax activation function, and hidden layers were used with Rectified Linear Activation (ReLU). All deep learning and deep hybrid learning models were trained for more than 14 epochs [4]. Authors in [17], [18] and [21] employed a new hybrid deep learning method; CNN-LSTM to effectively predict the health condition of each machine. In reference [9], a generative deep learning model based on the conditional variational autoencoder (CVAE) was proposed for a PdM-integrated production scheduling problem using large-scale industrial condition monitoring data. In reference [15], several models based on deep neural networks (DNN) and recurrent neural networks (RNN) were compared, using criteria based on visual analysis, errors, regression coefficient, and accuracy measures. Gour & Waoo [7] implemented an ensemble learning algorithm with a deep learning model to predict short-term and long-term health and failure. By incorporating the Light GBM, random forest and decision tree, a novel Ensemble Learning model combined with Deep Neural Network (EnDNN) has been framed. Aghamohmmadghasem et al. [33] utilized a deep reinforcement learning approach to solve the optimal maintenance planning problem in the inland waterway transportation system.

The DNN model which is proposed in this study comprises of multiple fully connected layers with ReLU activation functions to identify complex patterns in the data. It leverages features such as lagged emissions, rolling statistics, and time-based features to understand the changes in machine’s behavior. Ensuring the model generalizes well to new data, regularization techniques such as dropout and early stopping are used to prevent overfitting. The model's predictions provide insights into potential failures across all machines throughout the entire planning horizon.

2.4.4 Ca*tBoost Model*

CatBoost is a new gradient boosting algorithm that successfully works with categorical features with the lowest information loss. CatBoost differs from other gradient boosting algorithms. First, it uses ordered boosting, an efficient modification of gradient boosting algorithms, to overcome the problem of target leakage. Second, this algorithm is useful on small datasets. Third, CatBoost can handle categorical features. This handling is usually completed at the preprocessing phase and essentially consists of replacing the original categorical variables with one or more numerical values [36]. A search on the literature of machine failure and production planning integration reveals that no previous study has used CatBoost. In this research, the CatBoost model is tailored for predicting machine failures in a one-year planning horizon. After extensive data preparation, including the creation of lagged and rolling statistical features to capture time-based patterns in machine performance, it is then fine-tuned with strong regularization and cross-validated using Stratified K-Folds to ensure robustness. The model is further assessed on key performance metrics establishing that the model is able to detect machines likely to fail next, so that preventive maintenance can be planned.

2.5 Master Production Planning (MPP)

The main aim in MPP is to provide a clear production plan in the planning horizon that guides manufacturing activities, ensuring that the right product groups are made in the right quantities and at the right time to optimize the objective functions. It also aids in satisfying the customer demand, the management of inventory and minimizing production interuptions. In a production setting, fluctuating resource capacity restricts production line performance, and ignoring this fact renders planning inapplicable [37]. Although Master Production Scheduling (MPS) has been studied and used by both academia and industries for quite a long time, the real complexity involved in making a master plan when capacity is limited, when products have the flexibility of being made at different production lines, and when performance goals are tight and conflicting [38]. Reference [39] can be considered as a step of applying machine learning on master production scheduling, which has not gained any attention yet. MPP coordinates production activities with business goals, providing a strategic framework for managing demand, actual capacity, and inventory. In the current research work, we addressed the MPP problem in the context of the make to order (MTO) production environment. The objective is to find the optimal production quantity of each product group in-house and through outsourcing considering capacity fluctuation of the machines due to failures with the minimum cost imposed by the company considering that capacity extension and backorder are allowed.

2.6 Mathematical Modeling

A linear programming model has been introduced incorporating in-house and outsourcing production, dynamic capacity extension, and backorders with lead time as shown in Figure 1. The following notations are used in the model.

Decision Variables:

- $x_{p,t}^{in}$: Amount of product *p* to produce in-house in month *t*
- $x_{p,t}^{out}$: Amount of product *p* to outsource in month *t*
- $b_{p,t}^{k}$: Backorder of product *p* in month *t*, carried over from $t-k$ months ago (for *k*=1,2 where lead time is 2 months)
- $c_{p,t}^{ext}$: Capacity extension for in-house production of product *p* in month *t*, which takes effect in future months (i.e., the number of additional units of capacity added)

Parameters:

- $d_{p,t}$: Demand for product *p* in month *t*
- $r_{p,t}$: Remaining in-house production capacity for product *p* in month *t*
- $o_{p,t}$: Outsourcing capacity for product *p* in month *t*
- $c_{p,t}^{in}$: In-house production cost per unit for product *p* in month *t*
- $c_{p,t}^{out}$: Outsourcing production cost per unit for product *p* in month *t*
- $c_{p,t}^{b}$: Backorder cost per unit of product *p* in month *t*, with penalties increasing over time
- c_{p}^{ext}: Capacity extension cost per unit for product *p*
- lead_time = 2: Lead time for backorders in numerical example (in months)
- penalty_multiplier: Penalty multiplier for delayed backorders, increasing with time

The objective function (Z) in this integrated model aims to minimize the summation of the total cost, as shown in Eq. (1)

$$Z = \sum_{t\epsilon T} \sum_{p\epsilon P} (c_{p,t}^{in} \, . \, x_{p,t}^{in} + c_{p,t}^{out} \, . \, x_{p,t}^{out} + \sum_{k=1}^{Lead\ Time} c_{p,t}^{b} \, . \, b_{p,t}^{k} . \left(\text{penalty}_{\text{multiplier}}\right)^{k} + c_{p}^{ext} \, . \, c_{p,t}^{ext}) \qquad (1)$$

The first constraint (Eq. (2)) guarantees that the sum of the production (in-house and outsourced) plus backorders from previous months meet demand in each month.

$$x_{p,t}^{in} + x_{p,t}^{out} + \sum_{k=1}^{Lead\ Time} b_{p,t}^{k} = d_{p,t} \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (2)$$

In-House capacity constraint is presented in Eq. (3), where the amount produced in-house cannot exceed the remaining in-house capacity that resulted from our prediction ML algorithms, $r_{p,t}^{in}$ plus any capacity extension. The summation, $\sum_{e=1}^{t}$, refers to all months t, from month 1 to the current month t, in the planning horizon.

$$x_{p,t}^{in} \le r_{p,t}^{in} + \sum_{e=1}^{t} c_{p,e}^{ext} \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (3)$$

As mentioned in assumptions, Outsourcing is limited by outsourcing capacity.

$$x_{p,t}^{out} \le o_{p,t} \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (4)$$

Backorders for a product carried over from previous months should align with the backorders available from

earlier months (reflecting a lead time of 2 months). It is shown in Eq. (5) where $b_{p,t}^{1}$ and $b_{p,t}^{2}$ are backorders carried over from 1 and 2 month ago, respectively.

$$b_{p,t}^{1} = b_{p,\mathrm{t}-1}^{2} , \; b_{p,t}^{2} = b_{p,\mathrm{t}-1}^{1} \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (5)$$

Eq. (6) ensures that if backorders are older than 2 months, they must be met by capacity extension.

$$b_{p,t}^{2} \le c_{p,t}^{ext} \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (6)$$

Amount of in-house and outsourced production cannot be negative, as well as backorders.

$$x_{p,t}^{in}, x_{p,t}^{out}, b_{p,t}^{1}, b_{p,t}^{2} \ge 0 \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (7)$$

Additionally, non-negativity of capacity extensions is shown in the Eq. (8).

$$c_{p,t}^{ext} \ge 0 \quad \forall\, p\epsilon P , \forall\, t\epsilon T \qquad (8)$$

This linear programming (LP) model minimizes the total cost incurred from in-house production, outsourcing, backorders with penalties, and capacity extensions, subject to capacity constraints and demand satisfaction. The decision variables $x_{p,t}^{in}$ and $x_{p,t}^{out}$ determine how much of each product is produced in-house and outsourced, respectively, while adhering to production capacity, cost limitations and backorder lead times. $b_{p,t}^{k}$ and $c_{p,t}^{ext}$ determine the amounts of backorders carried over from previous months and the capacity extensions added to increase future in-house production, in corresponding order, while accounting for lead time constraints, backorder penalties, and the need to expand production capacity to meet future demand.

A critical aspect of the problem is that a portion of the in-house production capacity has been lost due to predicted machine failures, causing the remaining capacity, $r_{p,t}$, to fall below the nominal capacity of the machines. This reduction in capacity is predicted through ML models, which forecast potential machine failures over the planning horizon. To mitigate capacity shortages, the model allows for capacity extensions, $c_{p,t}^{ext}$, which provides flexibility to adjust future in-house production capacity.

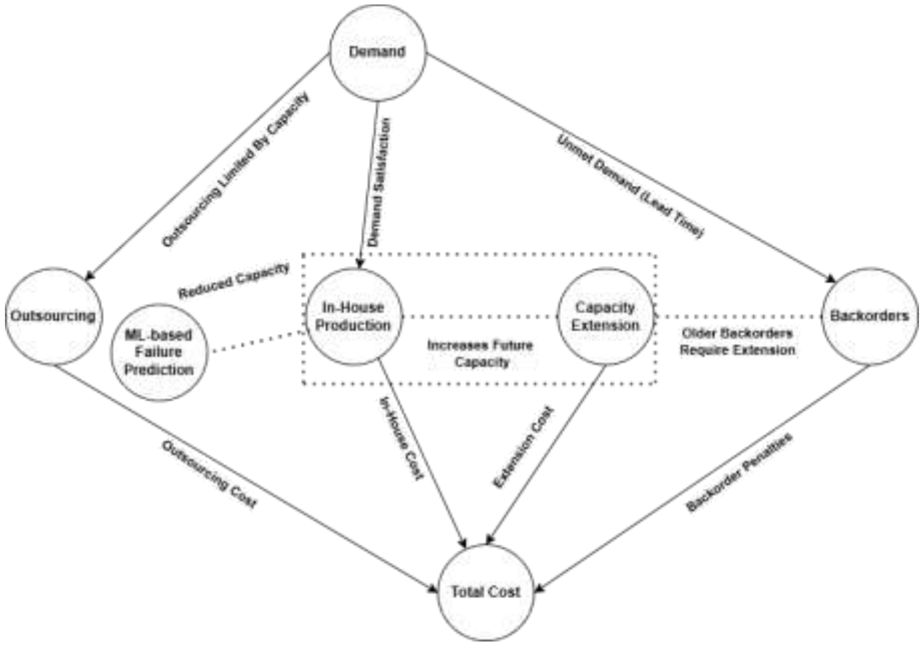

Fig. 1. *Dynamic linear programming model structure diagram*

2.7 Dynamic Process Flow

The model's ability to respond in fluctuating conditions in the production environment through a combination of lead time considerations, backorders, capacity adjustments, and outsourcing demonstrate the dynamic nature of the model. Backorders which introduce a delay in meeting customer demand because of insufficient production or capacity are vital elements in the model. Backorders are dynamically tracked across multiple months according to predetermined lead time of two months, reflecting real-world delays in this business. This is mathematically shown through the backorder variables b_(p,t)^1 and b_(p,t)^2, which represent the backorders carried over from 1 and 2 months ago, respectively. This approach ensures that any unmet demand in a given month m will be carried over and penalized, and the penalty factor increases over time. The backorder flow is thus no constant, it highlights both the unmet demand and the delay penalties, which force organizations to ensure timely production to minimize their total costs. Another dynamic feature is the model's ability to adjust in-house production capacity regarding the predicted failures of the machines and demand fluctuations. In-house production capacity, r_(p,t)^in , is sensitive to the predicted failures and could decline. These reductions lead to the fact that the nominal capacity may not always be available, which explains why flexibility in production is significant. To address capacity shortages, the model gives the possibility to the possibility of capacity extensions, c_(p,t)^ext, which allow for the dynamic expansion of future production capacity. We combine in-house production and outsourcing to allow for flexibility. Outsourcing helps quickly solve capacity shortages, but at a potentially higher cost. The model identifies the optimal level of in-house production and outsourcing so as to meet the demand without incurring high backorder costs and increasing cost.

3. NUMERICAL EXAMPLE/CASE STUDY

3.1 Dataset Description

To validate the proposed framework and mathematical model, historical data collected from the daily emergency forms were used: they were available in the maintenance software application that was filled by the expert in the maintenance department from April 2023 to March 2024. An example of the report from the maintenance software for the 26th of April is presented in Excel format that is shown in Table 2.

***Table 2**. Software report*

Date	Machine Coding	System-wide Failure	Component Failure	Maintenance Action	Start Time	Finish Time	Failure (min)	Maintenance (min)	Maintenance Responsible	Shift
26/04/2023	SCA202	Mechanical	Fireproof Failure	Replacement	05:50:00	06:15:00	25	20	Head Shift	Night
26/04/2023	SCA301	Mechanical	Settings Failure	Resetup	08:00:00	09:30:00	90	60	Head Shift	Day
26/04/2023	SCA202	Mechanical	Settings Failure	Resetup	09:00:00	12:00:00	180	120	Head Shift	Day
26/04/2023	SCA302	Mechanical	Blade Failure	Replacement	10:00:00	12:30:00	150	120	Supervisor	Day
26/04/2023	SCA201	Mechanical	Blade Failure	Replacement	20:00:00	23:00:00	180	120	Head Shift	Night

The report for the mentioned time period represents downtime events of 22 machines in 15 attributes. The attributes describing the machines were segmented into three categories as follows: machine specification (machine coding), failure information (including system-wide and component failures, maintenance actions and related responsible) and time values such as date, shift, start time, finish time, duration of downtime and net maintenance time which are used for developing our ML algorithms to forecast future failures.

As demonstrated in Figure 2, study starts with collecting data and ends with the evaluation of the trained ML models using performance metrics.

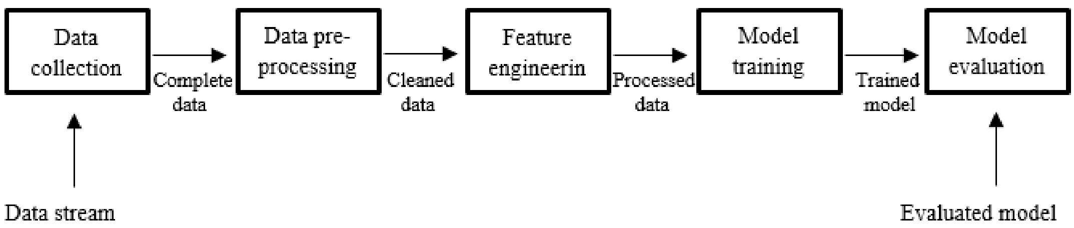

Fig. 2. *Data procedures*

3.2 Data Collection

The dataset used for the numerical example was obtained from operational data of the maintenance software application gathered over a year. Converting it to an Excel file, an initial failure dataframe was built.

3.3 Data Pre-Processing

Because each row is considered unique when at least one element in each column is different, the first occurrence of duplicated rows was kept and all others were removed. The Date, Start Time, and Finish Time columns were converted to the proper date-time format to ensure consistency and coerce invalid dates or times to NaT values. After creating the new unified Time columns, the original columns were dropped. Another key step in data cleansing is dropping rows where critical fields are missing or have null values. Finally, we ensure that non-numeric values were transformed into numeric.

3.4 Feature Engineering

To provide the model with valuable information such as historical patterns and cumulative behavior that improve its ability to predict machine failures, we added some features to the dataset. We extracted several time-related features from the raw timestamp data such as hour of the day, day of the week and month to identify temporal patterns. Lag features of experienced downtime were also introduced to enable the model to learn from the machine's recent downtime history which is often a good indicator of future failures. In addition to lag features, the rolling mean and sum of downtime were computed over multiple time windows (7, 14, and 30 days) to capture short-term trends. To reflect the long-term operational history of the machine, the total downtime is also calculated to provide a broader view of the machine's performance. In the final step of feature engineering, we created a binary target variable (WFS) that indicates whether a machine is likely to experience significant downtime in the near future. These features derived from existing time and downtime values, help the ML model capture both short-term and long-term patterns in failure behavior.

3.5 Model Training

We separately trained a binary classification model using SVM, LR, DNN and CatBoost algorithms. Using the train-test-split function from the scikit-learn library, the dataset was split into training and testing sets using an 80-20 proportion: 80% of the data used for training and 20% reserved for testing. In order to avoid overfitting during training process, we used techniques like hyperparameter tuning and early stopping. To ensure robust performance across different data splits, we employed stratified K-fold cross-validation with CatBoost. We also used a feature scaling class, StandardScaler from the scikit-learn library, to normalize the input features.

3.6 Model Evaluation

We used common standard metrics to assess the efficiency of our algorithms. The formulas for measuring accuracy, precision, recall and F1 score are as follows as mentioned in [7]:

$$Accuracy = \frac{tp + tn}{tn + tp + fp + fn} \tag{9}$$

$$Precision = \frac{tp}{tp + fp} \tag{10}$$

$$Recall = \frac{tp}{tp + fn} \tag{11}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{12}$$

Where true positives (tp) is the number of instances where the model correctly predicted the positive class. True negatives (tn) represents the number of instances where the model correctly predicted the negative class. False positives (fp) illustrates the number of instances where the model incorrectly predicted the positive class (also known as Type I error) and the number of instances where the model incorrectly predicted the negative class (also known as Type II error) is called false negatives (fp) [4]. We also used another usual performance metric named AUC (Area Under the Curve) to evaluate the quality of our binary classification models. Specifically, it measures the area under the ROC (Receiver Operating Characteristic) curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. It is a graphical representation that illustrates the diagnostic ability of the classifier as a discriminant threshold is varied [5].

4. RESULTS

In a real application of the proposed approach, we addressed the problem in the three specified scenarios using an Intel Core i5-5200U CPU, 8 GB RAM, Intel HD Graphics 5500 GPU, window 10 as the operating system.

Table 3 shows the performance of our ML models based on standard performance metrics. In addition, the highest values for each metric were highlighted among all algorithms. The DNN model achieves the best results across most evaluation metrics including Accuracy, Recall, F1-score, and AUC, while ranking second in Precision. Therefore, based on these findings, the DNN model is the most effective strategy in terms of performance metrics and superior to all three other algorithms.

Table 3. *Model evaluation*

	Standard performance metrics				
ML methods	Accuracy	Precision	Recall	F1 score	AUC
SVM	0.9484	0.9343	0.9275	0.9309	0.9442
LR	0.9490	0.9706	0.8919	0.9296	0.9965
DNN	**0.9796**	0.9730	**0.9730**	**0.9730**	**0.9969**
CatBoost	0.9000	**0.9924**	0.7318	0.8424	0.9959

The AUC train and test in DNN model are presented in the Figure 3 for 50 number of epochs. AUC ranges in value from 0 to 1 [7]. Train AUC is represented in baby blue color while the test AUC is shown in red color. As seen, both curves increase rapidly in the initial epochs, indicating the model is learning well, and they plateau around an AUC score of 0.99, which highlights excellent performance.

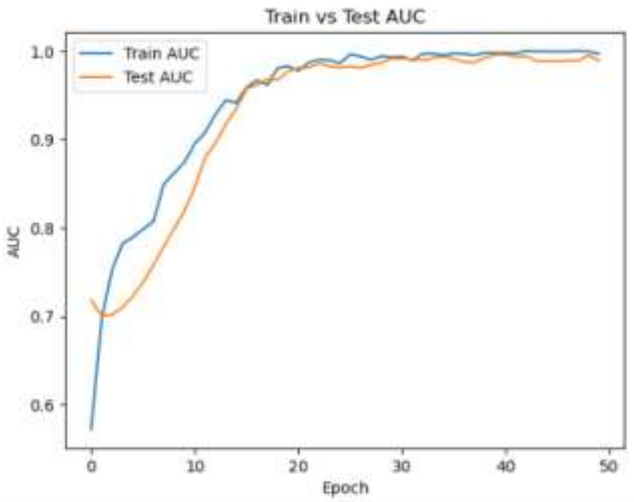

Figure. 3. *Training vs Test AUC*

4.1 Dynamic linear programming (DLP) illustrative example

Let us optimize production decisions for the 7 product groups mentioned in section 2 over a 12-month planning horizon. The objective is to minimize total costs, including in-house production, outsourcing, backorders, and capacity extensions, while meeting monthly demand. Three scenarios (S1, S2 and S3) are considered that differ in machine failure calculations. The first scenario is the one presented in the original problem. In the second scenario, we assumed that machine failure values are 50 percent higher than the estimated values. And in the third one, the problem is solved without machine failures, assuming that no machine capacity is lost due to breakdowns.

Table 4 gives a summary of the costs. We used the latest real production costs and procurement prices for in-house and outsourcing costs for each product group. To reflect the actual cost of production for backorders without adding unnecessary complexity, we assumed backorder cost as the average of in-house and outsourcing costs, which indicates a penalty cost for delaying fulfillment of the demand. Our rough calculations for equipment and infrastructure needed for capacity expansion have led us to the costs of capacity extension per unit of each product group in the last column of the table. Distribution of demand for each product group for 12 months planning period is presented in table 5.

Table 4. *Production cost*

P ID	Product group	In-house cost per unit ($)	Outsourcing cost per unit ($)	Backorder cost per unit ($)	Capacity extension cost per unit ($)
1	Sheet Freezer Bag	2.25	2.43	2.34	62.5
2	Freezer Bag Roll	1.4	1.54	1.47	70
3	Dispenser Box Freezer Bag	2.3	2.65	2.475	65
4	Garbage Bag Roll	0.75	0.795	0.7725	50
5	Easy Tie Garbage Bag	1.18	1.28	1.23	55
6	Plastic Disposable Tablecloth	1.86	3.55	2.705	75
7	Disposable Glove	2.2	2.45	2.325	55

The nominal in-house production capacity, as well as the outsourcing production capacity, for each product group are presented in Table 6. As can be seen, the nominal production capacity is assumed to be constant across all months. However, the remaining in-house production capacity, $r_{p,t}$, is calculated by deducting the predicted downtimes obtained from ML models from the nominal capacity.

Table 5. *Demand quantities (per carton)*

	Months											
P ID	1	2	3	4	5	6	7	8	9	10	11	12
1	4,610	5,809	6,008	5,916	6,962	7,133	6,205	5,926	6,315	7,239	7,667	8,530
2	3,601	5,450	4,746	4,176	4,663	4,507	5,023	4,704	5,147	6,460	6,678	5,621
3	2,512	4,146	4,533	7,251	4,334	4,392	5,888	3,685	4,785	7,193	6,803	7,358
4	7,304	10,195	10,137	9,845	10,497	10,780	11,707	10,460	11,059	12,160	13,370	13,570
5	3,611	5,570	6,049	5,207	5,472	5,372	5,187	4,628	4,549	5,674	4,984	5,507
6	6,755	8,300	7,175	7,936	7,701	8,359	7,555	7,020	7,288	8,907	9,592	10,215
7	658	1,507	1,640	1,462	1,700	1,369	1,591	1,338	2,028	1,963	2,402	1,734

The optimal master production plan for each product over a 12-month future planning horizon for all scenarios utilizing the DNN algorithm is presented in Table 7 to 13. The tables show the amount of in-house production, outsourcing, any necessary capacity extensions, the backordered quantities in carton, and the associated total costs. These results were obtained using a DLP model programmed in Python utilizing the SciPy linprog solver with the Highs method. As seen in the tables, the DLP process dynamically balances production allocation decisions across months for different product groups to minimize overall cost, considering fulfillment of demand and available or future production capacity in the proposed scenarios.

Figure 4 provides a detailed view of the decision variables (summation of product groups) as well as the optimal production planning strategy during a 12-month planning horizon for three scenarios (S1, S2, and S3). We see stable in-house production levels that have a gradually increasing trend across the planning horizon. Notably, in the last months, values of S2 are slightly lower than S1 and S3. This suggests that in this particular scenario, resources may have been reallocated to other strategies such as outsourcing or capacity expansion because of capacity loss from machine failures. This trend supports the key role of in-house production as the main base to meet demands with only minor adjustments.

Table 6. *In-house and outsourcing capacity (per carton)*

ID	In-house	Outsourcing
1	4,480	1,250
2	4,200	500
3	6,000	300
4	8,800	750
5	4,800	200
6	7,800	250
7	960	300

Table 7. *Optimal production plan and total costs for sheet freezer bag in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	4467,4454,4480	143,156,130	0,0,0	0,0,0	10398.24,10400.58, 10395.9
2	4480,4480,4480	1250,1250,1250	0,0,0	79,79,79	13302.36, 13302.36,13302.36
3	4443,4406,4480	1250,1250,1250	0,0,0	394,431,357	13956.21,13959.54,13952.88
4	4476,4472,4480	1250,1250,1250	584,625,543	0,0,0	49608,52162.5,47055
5	5017,5012,5023	1250,1250,1250	0,0,0	695,700,689	15952.05,15952.5,15951.51
6	5033,5042,5023	1250,1250,1250	0,0,0	1545,1541,1549	17977.05,17987.94,17963.91
7	5021,5019,5023	1250,1250,1250	1479,1477,1481	0,0,0	106772.25,106642.8,106901.8
8	5926,۵۹۲۶,5926	0,0,0	0,0,0	0,0,0	13333.5,1333.5,1333.5
9	6315,6315,6315	0,0,0	0,0,0	0,0,0	14208.75,14208.75,14208.75
10	6540,6577,6504	699,662,735	0,0,0	0,0,0	16413.57,16406.91,16420.05
11	6527,6550,6504	1140,1117,1163	0,0,0	0,0,0	17455.95,17451.81,17460.09
12	6533,6563,6504	1250,1250,1250	0,0,0	747,717,776	19484.73,19482.03,19487.34
Total	64778,64816,64742	10732,10685,10778	2063,2102,2024	3460,3468,3450	308863.16,311290.67,306433.04

Table 8. *Optimal production plan and total costs for freezer bag roll in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	3601,3601,3601	0,0,0	0,0,0	0,0,0	5041.4,5041.4,5041.4
2	4178,4156,4200	500,500,500	0,0,0	772,794,750	7754.04,7755.58,7752.5
3	4196,4193,4200	500,500,500	0,0,0	822,847,796	7852.74,7885.29,7820.12
4	4200,4200,4200	500,500,500	298,323,272	0,0,0	27510,29260,25690
5	4430,4388,4472	233,275,191	0,0,0	0,0,0	6560.82,6566.7,6554.94
6	4479,4485,4472	28,22,35	0,0,0	0,0,0	6313.72,6312.88,6314.7
7	4491,4510,4472	500,500,500	0,0,0	0,13,51	7104.44,7103.11,7105.77
8	4486,4499,4472	250,218,283	0,0,0	0,0,0	6665.4,6634.32,6696.62
9	4475,4477,4472	500,500,500	0,0,0	172,170,175	7287.84,7287.7,7288.05
10	4452,4430,4472	500,500,500	1680,1700,1663	0,0,0	124602.8,125972,123440.8
11	6165,6196,6135	500,482,500	0,0,0	13,0,43	9420.11,9416.68,9422.21
12	5634,5621,5664	0,0,0	0,0,0	0,0,0	7887.6,7869.4,7929.6
Total	54787,54756,54832	4011,3997,4009	1978,2023,1935	1811,1824,1815	224000.91,227105.06,221056.71

Table 9. *Optimal production plan and total costs for dispenser box freezer bag in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	2512,2512,2512	0,0,0	0,0,0	0,0,0	5777.6,5777.6,5777.6
2	4146,4146,4146	0,0,0	0,0,0	0,0,0	9535.8,9535.8,9535.8
3	4533,4533,4533	0,0,0	0,0,0	0,0,0	10425.9,10425.9,10425.9
4	5966,5932,6000	300,300,300	0,0,0	985,1019,951	16954.675,16960.63,16948.73
5	5319,5353,5285	0,0,0	0,0,0	0,0,0	12233.7,12311.9,12155.5
6	4392,4392,4392	0,0,0	0,0,0	0,0,0	10101.6,10101.6,10101.6
7	5888,5888,5888	0,0,0	0,0,0	0,0,0	13542.4,13542.4,13542.4
8	3685,3685,3685	0,0,0	0,0,0	0,0,0	8475.5,8475.5,8475.5
9	4785,4785,4785	0,0,0	0,0,0	0,0,0	11005.5,11005.5,11005.5
10	5954,5908,6000	300,300,300	0,0,0	939,985,893	16813.225,16821.28,16805.18
11	5977,5955,6000	300,300,300	1465,1533,1396	0,0,0	109767.1,114136.5,105335
12	7358,7358,7358	0,0,0	0,0,0	0,0,0	16923.4,16923.4,106923.4

Total	60515,60447,60584	900,900,900	1465,1533,1396	1924,2004,1844	241556.4,246018,237032.1

Table 10. *Optimal production plan and total costs for garbage bag roll in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	7304,7304,7304	0,0,0	0,0,0	0,0,0	5478,5478,5478
2	8783,8767,8800	750,750,750	0,0,0	662,678,645	7694.895,7695.255,7694.513
3	8800,8800,8800	750,750,750	0,0,0	1249,1265,1232	8161.1025,8173.463,8147.97
4	8800,8800,8800	750,750,750	1544,1560,1527	0,0,0	84396.25,85196.25,83546.25
5	10344,10360,10327	153,137,170	0,0,0	0,0,0	7879.635,7878.915,7880.4
6	10269,10210,10327	511,570,453	0,0,0	0,0,0	8107.995,8110.65, 8105.385
7	10327,10327,10327	750,750,750	0,0,0	630,630,630	8828.175,8828.175,8828.175
8	10327,10327,10327	750,750,750	0,0,0	13,13,13	8351.543,8351.543,8351.543
9	10311,10293,10327	750,750,745	11,29,0	0,0,0	8879.5,9766,8337.525
10	10355,10389,10327	750,750,750	0,0,1083	1055,1021,0	9177.4875,9176.723,62491.5
11	10288,10256,11410	750,750,750	0,0,0	3387,3385,1210	10928.7075,10903.16,10088.48
12	10330,10339,11410	750,750,750	5877,5866,0	0,0,2620	302193.75,301650.5,11177.7
Total	116238,116172,118486	7414,7457,7368	7432,7455,2610	6996,6992,6350	464599.04,471208.635,230127.435

Table 11. *Optimal production plan and total costs for easy tie garbage bag in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	3611,3611,3611	0,0,0	0,0,0	0,0,0	4260.98,4260.98,4260.98
2	4794,4788,4800	200,200,200	0,0,0	576,582,570	6621.4,6621.7,6621.1
3	4800,4800,4800	200,200,200	0,0,0	1625,1631,1619	7918.75,7926.13,7911.37
4	4800,4800,4800	200,200,200	1832,1838,1826	0,0,0	106680,107010,106350
5	5472,5472,5472	0,0,0	0,0,0	0,0,0	6456.96,6456.96,6456.96
6	5372,5372,5372	0,0,0	0,0,0	0,0,0	6338.96,6338.96,6338.96
7	5187,5187,5187	0,0,0	0,0,0	0,0,0	6120.66,6120.66,6120.66
8	4628,4628,4628	0,0,0	0,0,0	0,0,0	5461.04,5461.04,5461.04
9	4549,4549,4549	0,0,0	0,0,0	0,0,0	5367.82,5367.82,5367.82
10	5674,5674,5674	0,0,0	0,0,0	0,0,0	6695.32,6695.32,6695.32
11	4984,4984,4984	0,0,0	0,0,0	0,0,0	5881.12,5881.12,5881.12

12	5507,5507,5507	0,0,0	0,0,0	0,0,0	6498.26,6498.26,6498.26
Total	59378,59372,59384	600,600,600	1832,1838,1826	2201,2213,2189	174301.27,174638.95,173963.59

Table 12. *Optimal production plan and total costs for plastic disposable tablecloth in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	6755,6755,6755	0,0,0	0,0,0	0,0,0	12564.3,12564.3,12564.3
2	7773,7746,7800	250,250,250	0,0,0	277,304,250	16094.565,16117.38,16071.75
3	7452,7479,7425	0,0,0	0,0,0	0,0,0	13860.72,13910.94,13810.5
4	7800,7800,7800	136,136,136	0,0,0	0,0,0	14990.8,14990.8,14990.8
5	7701,7701,7701	0,0,0	0,0,0	0,0,0	14323.86,14323.86,14323.86
6	7741,7682,7800	250,250,250	0,0,0	368,427,309	16281.2,16331.06,16231.345
7	7743,7685,7800	180,250,64	0,47,0	0,0,0	15040.98,18706.6,14735.2
8	7020,7020,7020	0,0,0	0,0,0	0,0,0	13057.2,13057.2,13057.2
9	7288,7288,7288	0,0,0	0,0,0	0,0,0	13555.68,13555.68,13555.68
10	7800,7847,7800	250,250,250	857,810,857	0,0,0	79670.5,17673.97,79670.5
11	8640,7813,8657	250,250,250	0,0,0	702,2339,685	18856.81,21746.68,18842.445
12	8635,7803,8657	250,250,250	0,4501,0	2032,0,1993	22445.16,352976.1,22380.585
Total	92348,90619,92503	1566,1636,1450	857,4548,857	3379,3880,3237	250741.775,525954.54,250234.17

Table 13. *Optimal production plan and total costs for disposable glove in all scenarios*

Month	In-house Production (S1-S2-S3)	Outsource Production (S1-S2-S3)	Capacity Extension (S1-S2-S3)	Backorder (S1-S2-S3)	Total Cost ($) (S1-S2-S3)
1	658,658,658	0,0,0	0,0,0	0,0,0	1447.6,1447.6,1447.6
2	949,938,960	300,300,300	0,0,0	258,269,247	3422.65,3424.025,3421.275
3	932,904,960	300,300,300	0,0,0	666,705,627	4333.85,4362.925,4304.775
4	960,960,960	300,300,300	868,907,829	0,0,0	50587,52732,48442
5	1700,1700,1700	0,0,0	0,0,0	0,0,0	3740,3740,3740
6	1369,1369,1369	0,0,0	0,0,0	0,0,0	3011.8,3011.8,3011.8
7	1591,1591,1591	0,0,0	0,0,0	0,0,0	3500.2,3500.2,3500.2
8	1338,1338,1338	0,0,0	0,0,0	0,0,0	2943.6,2943.6,29436
9	1804,1820,1789	224,208,239	0,0,0	0,0,0	4517.6,4513.6,4521.35
10	1813,1838,1789	150,125,174	0,0,0	0,0,0	4356.1,4349.85,4362.1

11	1821,1852,1789	300,300,300	0,0,0	281,250,313	5394.525,5390.65,5398.525
12	1828,1867,1789	187,117,258	0,0,0	0,0,0	4479.75,4394.05,4567.9
Total	16763,16835,16692	1761,1650,1871	868,907,829	1205,1224,1187	91734.675,93810.3,89661.125

There are large variations over months as seen in outsource production subplot. Peaks in different months signify more reliance on outsourcing to meet demand because full utilization of in-house capacity was occurred. Earlier capacity extensions lead to significant drop in outsource values in months 5 and 8 for all scenarios. These variations in levels of outsourcing suggest that outsourcing can be viewed as a flexible mechanism to cope with spikes in demand when in-house capacity is insufficient.

Periods where demand exceeds available supply are shown in the third subplot that result in backorders. For instance, backorders reach the highest level in month 3 in all scenarios possibly due to a rise in demand or capacity constraints. Another peak in month 11 especially high for S2 means that postponing the orders is more cost- effective.

The capacity extension trends shown in the fourth subplot are other examples of addressing demand variations. As discussed earlier, investment to increase the manufacturing capacity is seen in month 4 which is clearly reflected in the same pattern of the total cost in Figure 6. A further peak is observable in the 12th month of the S2 applying capacity extension at the end of the planning horizon.

The stacked area charts in Figure 5 represent the cumulative contributions of in-house production, outsource production, capacity extension, and backorders across a 12-month period for our scenarios. In S1, in-house production in blue color remains high with steady increase throughout the year. Outsource production which is colored orange plays a secondary role with an increasing trend toward the end of the year, indicating some reliance on external resources when internal capacity is unable to satisfy the demand. Capacity extension depicted in green shows minimal fluctuations. This means that internal production capacity in S1 is almost adequate. The backorders indicated in red maintained stable meaning that overall demand is adequately and consistently fulfilled.

While internal production dominates the S2, a small growth of outsource production can be observed in contrast to the S1. This scenario depends more on external production to meet demand. Interestingly, the importance of capacity extension increases here. The capacity is extended where needed. Backorders remain low through S2 similar to S1 although they rise again later in the year.

In S3, in-house production continues to dominate, but the pattern is different. Outsource production plays a much smaller role compared to the other scenarios because of fully usage of internal capacity. This means that S3 relies heavily on internal resources rather than external sourcing. Capacity extension is moved forward and values are higher during the last months in comparison with the previous two scenarios. Here, backorders are the least in all the three strategies indicating little unfulfilled demand.

In general, our scenarios show distinct approaches to the management of production. S1 implements a balanced strategy in terms of internal production activities and external resource dependency. S2 shifts toward greater external resources, with a moderate role for capacity extension. S3 is the one with the greatest focus on internal production which leads to substantial in-house production, occasional capacity adjustments and thus lower backorders. Such distinctions can be considered as different management approaches employed by the firms; S3 relies on own capacity, S2 opts for external sources, while S1 employs stable moderate strategies.

Finally, the total monthly and cumulative costs associated with each scenario are depicted in Figure 6. In the top subplot, we see a significant cost increase in month 4 that exactly corresponds to the capacity extension peak shown in Figure 4. This suggests the financial impact of capacity expansion in all scenarios. As can be seen, in the seventh month, the total costs are exactly proportional to the amount of capacity extension in Figure 4. Another increase is also evident in month 12, especially for scenario S2, implies that the model attempts to meet end-of-year demands. In the bottom subplot, S2 accumulates the highest total cost by the end of the period, showing a consistent increase throughout due to the high share of cumulative capacity extensions. S1 also rises steadily, but with some fluctuations, reaching a cumulative cost higher than that of third scenario. S3 despite its occasional spikes especially in the last month, accumulates the least total cost by the end of the period. This suggests that S3 maintains lower cumulative costs compared to the other two scenarios, because it relies heavily on inexpensive internal production.

5. DISCUSSION

In contrast to existing literature that often uses environmental variables of machines and components or well-known datasets, we utilize event-based historical data of machine failures with a two-level classification (system and component) to predict future failures. Furthermore, unlike previous studies that have focused on integrating failure data with production planning primarily at the scheduling and planning levels, our research models this integration at the broader master production level within a real multi-machine system across several product groups. The main analytical outcomes of this research are as follows:

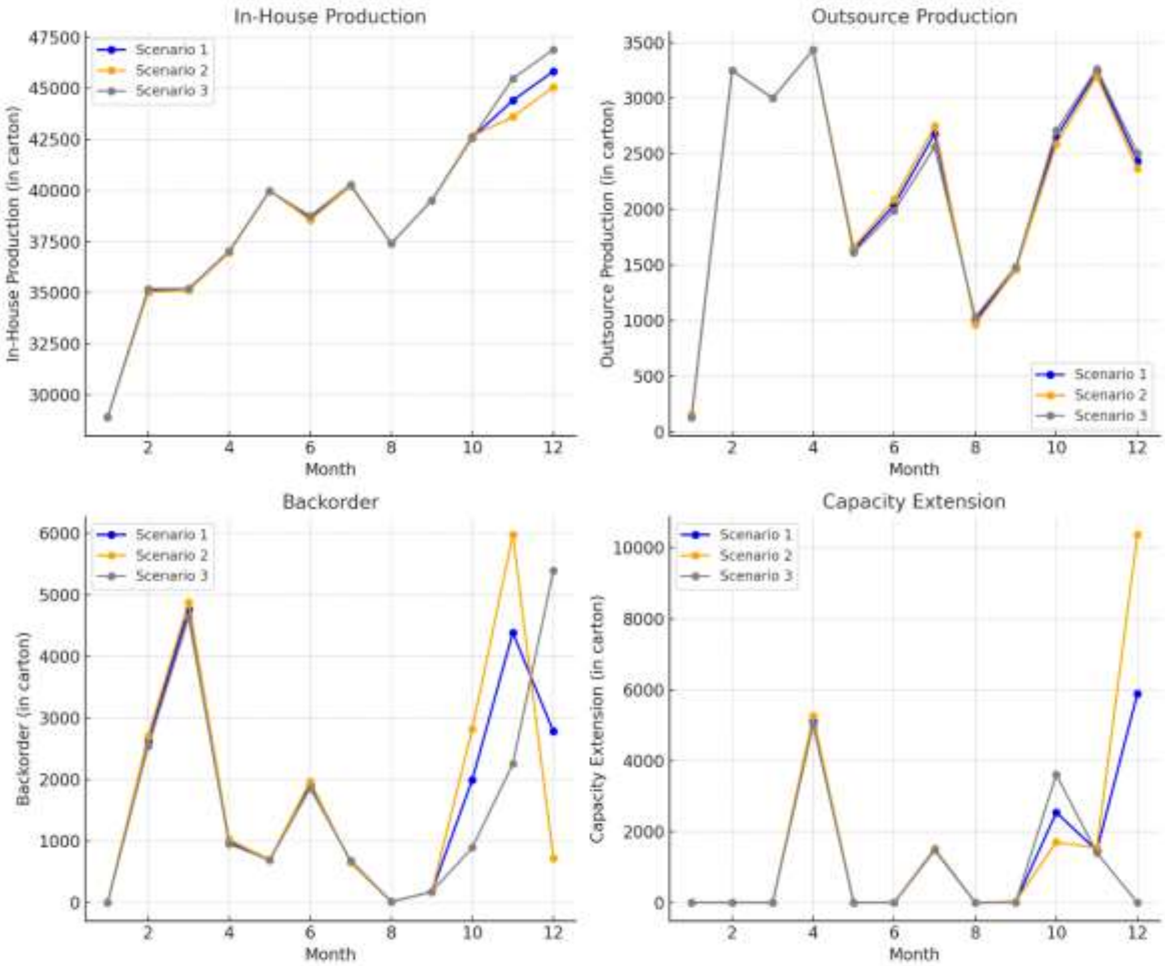

Figure. 4. *Scenario-based analysis of decision variables*

5.1 Enhancing Maintenance Decision-Making

This research enhances maintenance decision-making by providing insights not only into when and for how long failures are likely to occur, but also which specific machines and components are at risk, and the potential causes of these failures. This enables the maintenance team to plan daily tasks effectively, allocate resources more efficiently and mitigate the risk of downtime. As shown in Figure 7, failure prediction results of the DNN algorithm indicate that the largest share of machine downtimes is due to mechanical failures, followed by electrical failures, with pneumatic failures accounting for a negligible proportion. Knowledge of the key factors of system-wide failures helps the maintenance manager in prioritizing training activities and recruitment needs. The comparison of the predicted percentage of failure for different components throughout the planning horizon is also shown in Figure 8. More than 60% of machine failures are due to five main causes including machine settings, cutting blades, perforating blades, ovens, and plastic rollers failures. This analysis ensures the team that all the necessary spare parts are available.

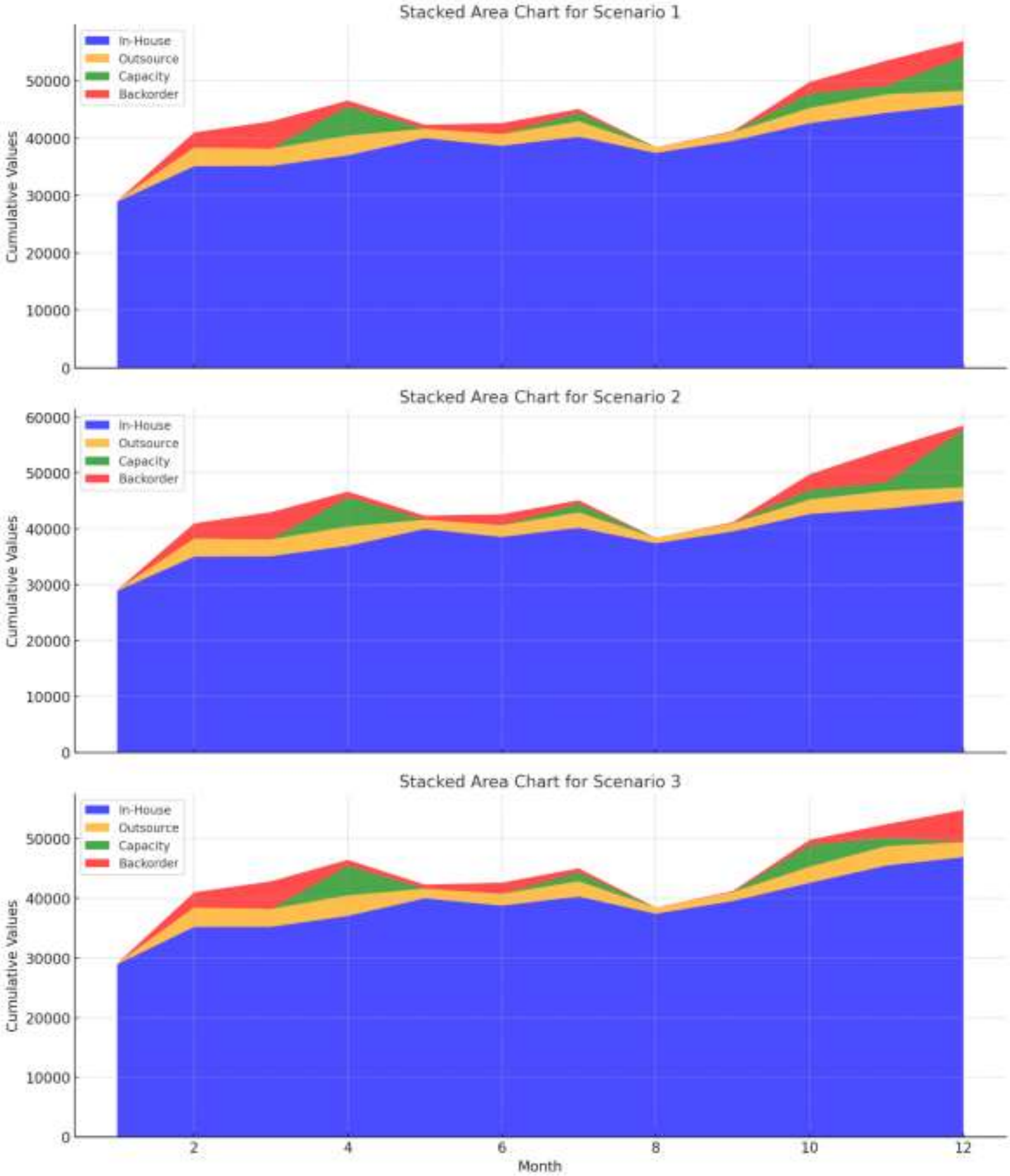

Figure. 5. *Stacked area chart for all scenarios*

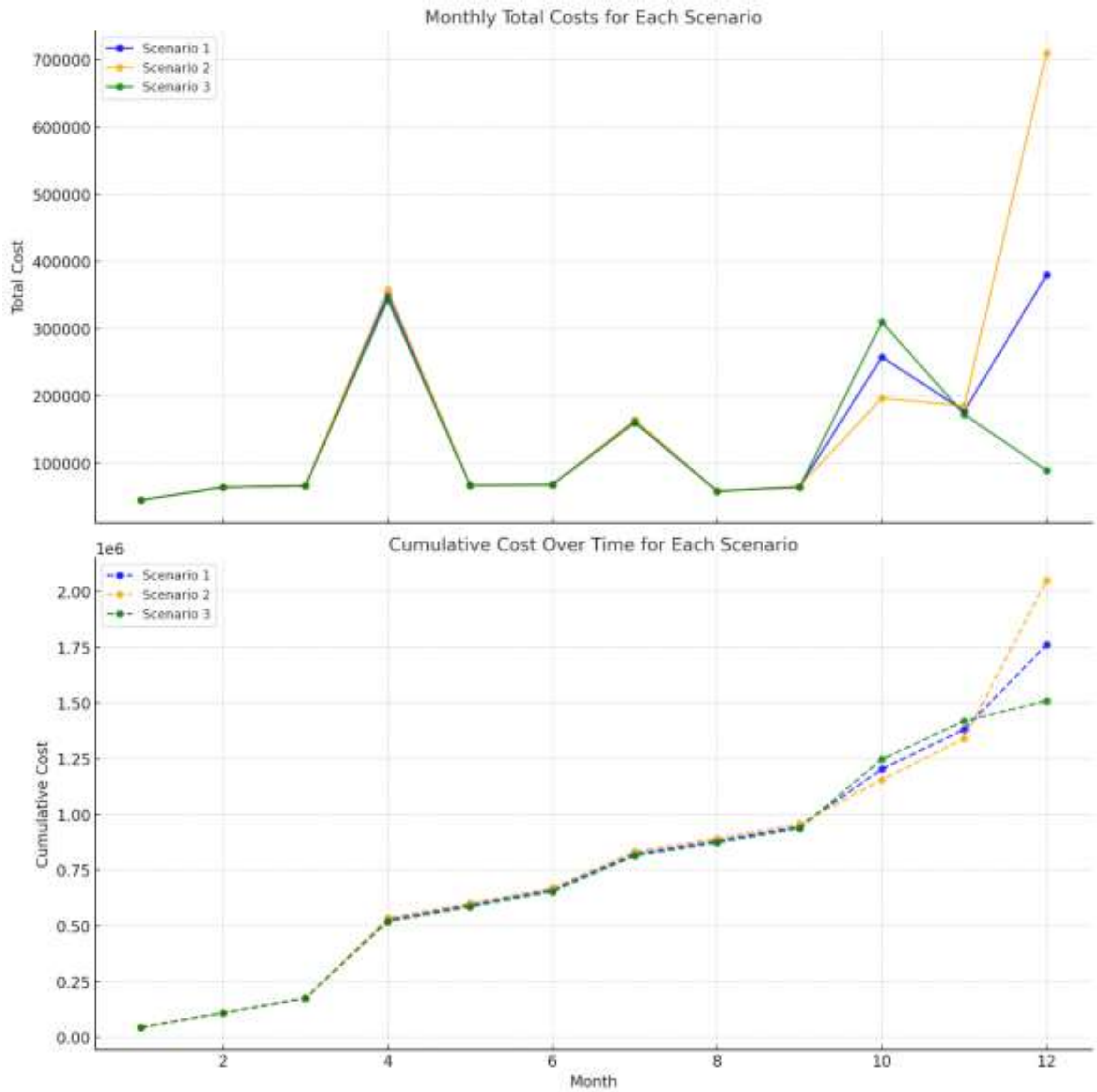

Figure. 6. *Monthly cost trend and cumulative cost over months*

These are two examples of analyses designed for the maintenance manager. Certainly, by analyzing the predicted failure results in more detail, such as examining a specific machine at a specified time, the maintenance team can make better use of this data. As a result, with early awareness of failure timing and causes, the gap between machine downtime due to failure and the machine repair or maintenance time can be reduced that leads to enhanced operational efficiency and reduced maintenance-related costs.

5.2 Selecting Master Production Strategies

In contrast to traditional MPP methods that rely on static assumptions regarding production capacity, our model adjusts production plans based on anticipated machine failures and thus dynamic changes in production capacity. For instance, if a failure is predicted, our model suggests adjustments in production quantities or proposes backordering. Additionally, when internal capacity is projected to be insufficient, the model recommends outsourcing strategies or capacity extensions to meet demand in advance. We presented three scenarios to provide managerial insight into the management of backorders, capacity extensions and outsourcing strategies. This research highlights distinct strategies available to production planning managers for addressing demand and capacity fluctuations. S3 with zero machine failures, suggests maximum in-house production as shown in Figure 9, because it focuses on self-reliance and minimizes backorders and external dependencies. This approach is ideal for factories where internal capacity is abundant and reliable. Lower production costs and more control over production processes are seen in this case. In contrast, S2, with considerable capacity loss due to failures, shows greater reliance on capacity extension and results in more backorders. Although this strategy offers more flexibility in satisfying demand, it comes at a higher cost. S1 represents a balanced approach, relying primarily on in-house production with limited external production. This strategy enables managers to run production lines steadily with occasional outsourcing in case of shortages in capacity. Surprisingly, as shown in Figure 9, in terms of unmet demand throughout planning horizon, S2 is the most successful in minimizing it. These unmet demands correspond to the 12th month of the scenarios, where S2 has achieved the lowest backorder as seen in Figure 4, or in fact, the lowest unmet demand. Our model provides valuable insights for production planning managers in choosing their production strategy, particularly in industrial environments where machine reliability is uncertain.

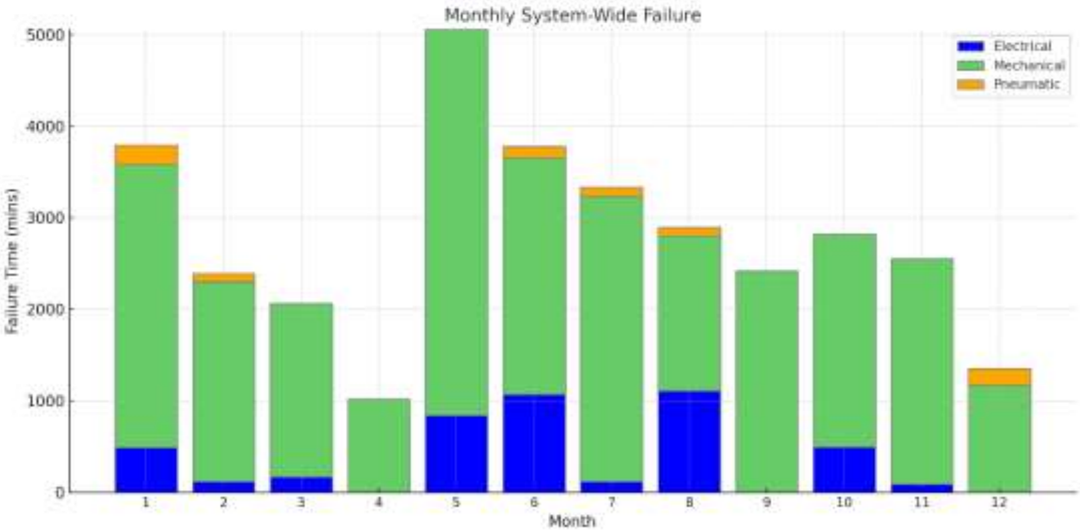

Figure. 7. *System-wide failure throughout planning horizon*

5.3 Optimizing Cost of production

The analysis of the three scenarios (S1, S2, and S3) reveals the impact of machine failures on the correlation of various production costs with the total cost. The first scenario as shown in the first subplot of Figure 10 depicts the baseline condition presents a relatively moderate relationship between in-house production cost (0.36), outsourcing cost (0.30), capacity extension cost (0.89) and backorder cost (0.46) and total cost. In this scenario, machine failures are rather moderate regarding to the overall impact on production costs, but capacity extension becomes the key issue.

In S2 where machine failures are increased by 50%, the correlations of in-house production costs (0.67), capacity extension costs (0.95), and backorder costs (0.80) rise significantly. This is due to the fact that machine failures have a larger effect on the total production cost. The value reduces slightly reaching to 0.19 in the right subplot of the heatmap which shows that outsourcing loses its precedence under higher machine failure conditions. The importance of capacity extension and backorder costs is high in S2 and they are the dominant contributors to total costs. On the other hand, the role of outsourcing costs is insignificant.

In S3 with no machine failure, in house production cost has a strong significant positive relation with total cost. The value of 083 suggests that the in-house production cost plays a more pronounced role. The correlations for capacity extension and backorder costs decreased to 0.6 and 0.73. The need for capacity extension and backordering is reduced because there are no machine failures. Outsourcing costs (0.61) increase in relevance. This indicates that in an uninterrupted production system, there is a tendency to outsource in capacity shortages.

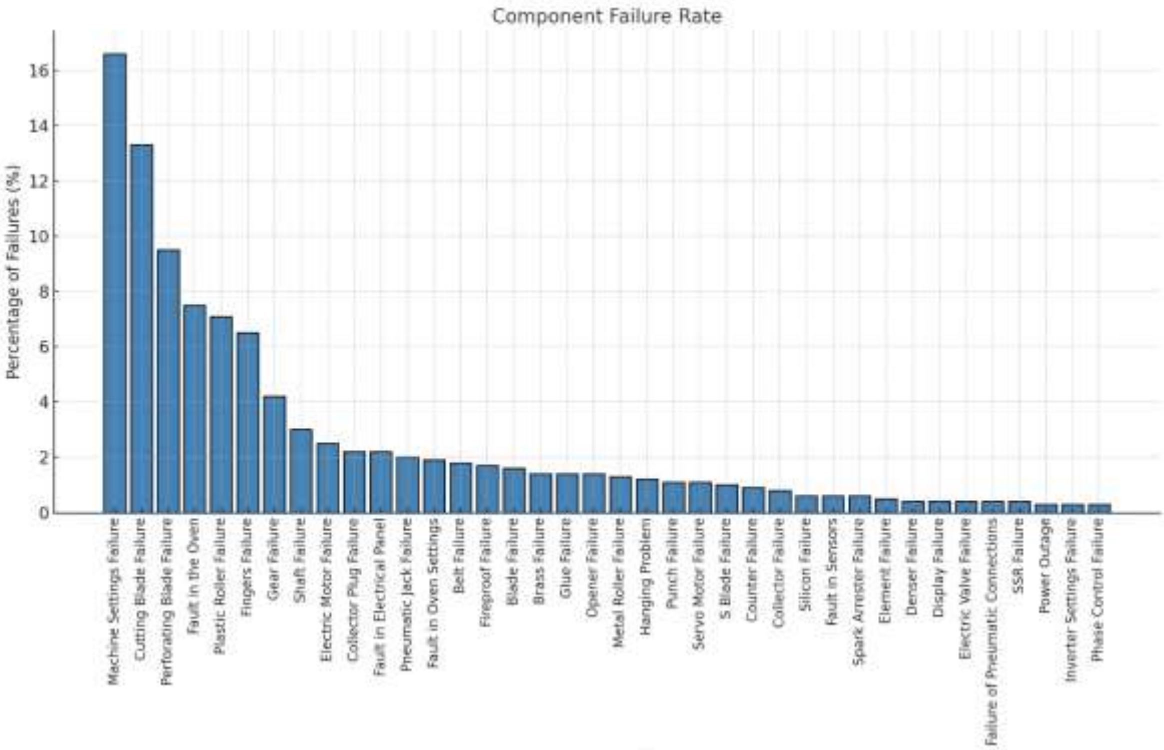

Figure. 8. *Predicted percentage of failure for each component*

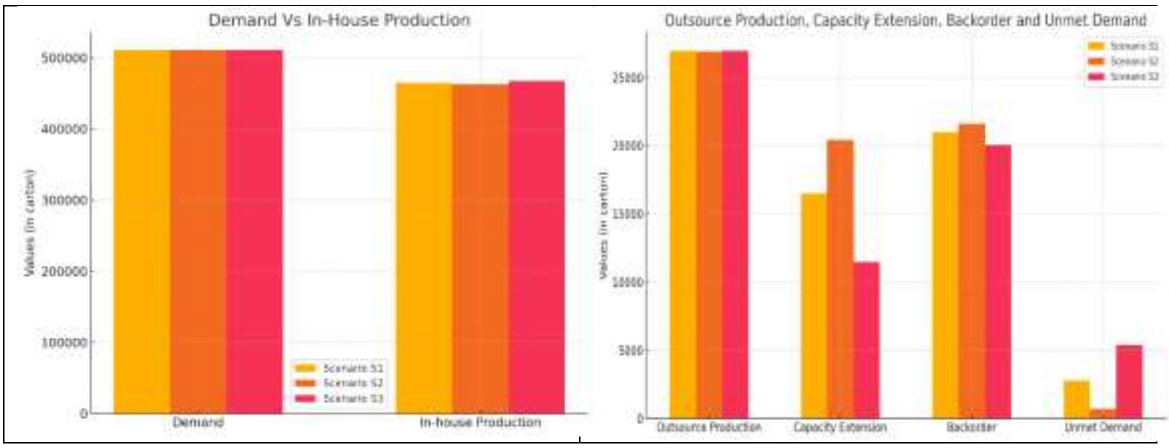

Figure. 9. *Sum of optimized production variables in the Scenarios*

In our proposed framework, the overall total cost has a substantial dependency on reliability of machines. Machine failures have a strong influence on cost structure, increasing the relevance of capacity extension and backorder costs. Removing these failures stabilizes the cost drivers, making in-house production and outsourcing more significant. Our model helps management identify cost drivers and plan for strategic decisions considering from a cost perspective.

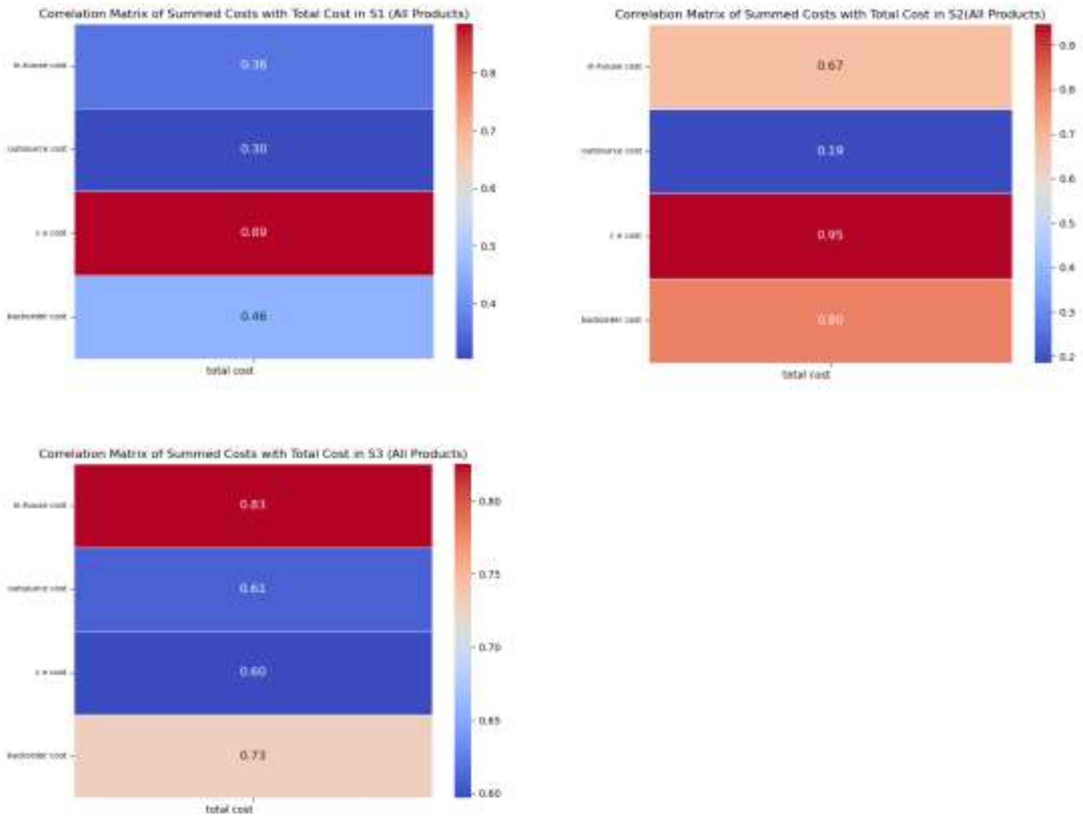

Figure. 10. *Heatmap of correlation between various production costs and the total cost*

5.4 Evaluating different lead times

Understanding the relationship between lead times and key variables equips managers with actionable insights to enhance supply chain efficiency and adapt to dynamic market conditions. Therefore, we examine its impact on our key decision variables. As shown in Figure 11, the impact of lead time on in-house production reveals stable trends in all scenarios with slight variations. Therefore, the stability of in-house production across scenarios highlights its role as a foundational strategy for meeting demand. But, the impact of lead time on outsource production, capacity extension, backorder, and unmet demand indicates distinct trends that vary across scenarios. In all scenarios as seen in Figure 12, outsource production decreases steadily as lead time increases. This means that having longer lead times allows internal resources to play a significant role and reduce the reliance on outsourcing. Capacity extension displays a scenario-specific pattern. In S1, it increases sharply at LT=4, suggests reaction to satisfy demand, whereas in S2 it peaks at LT=2 before declining. In S3, capacity extension rises progressively.

However, backorders and unmet demand trends are the most important in Figure 12 Both backorder and unmet demand grow consistently with lead times in all scenarios. There is a sharp rise at LT=4 except for unmet demand in the second scenario. Managing demand gets challenging by increasing lead time. Managers could explore several strategies to lessen this challenge. Persuading the customers to accept delivery of orders after certain specified dates would help to reduce the pressure on the supply chain. This transparent communication with customers for delays may also enhance their level of trust and ability to accept longer lead times. Additionally, backorders can be mitigated by investing in agile production or improving demand forecast.

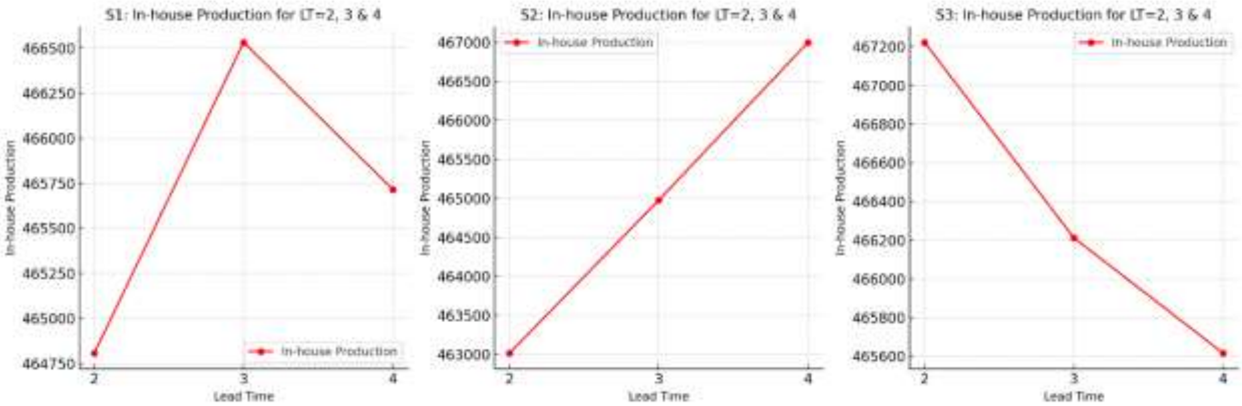

Figure. 11. *In-House production trend across different lead times*

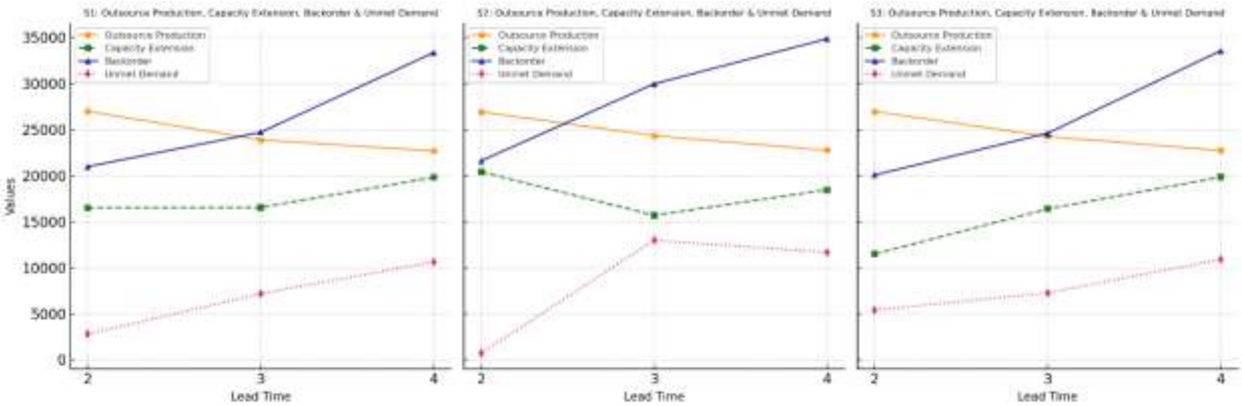

Figure. 12. *Outsource production, capacity extension, backorder and unmet demand trends across different lead times*

6. CONCLUSION AND FUTURE RESEARCH

This paper tackles the problem of integrating MPP and failure prediction in a real-world multi-machine packaging system. The main focus of the study is the development of an innovative framework to predict the machine failures in the next planning horizons and optimize production planning. To achieve this, we introduced a binary target variable called WFS to forecast downtime in future planning horizons. Using this variable, we built ML models to forecast the machines' probable failures so that effective maintenance could be planned in advance to improve the master production plans. Following an evaluation of 4 ML models' effectiveness using standard performance metrics, the optimal model was selected. Our evaluation demonstrated that while all the models performed effectively, the Deep Neural Network (DNN) model consistently outperformed the others. Based on this model, we calculated the remaining capacity, which was then utilized as an input for the subsequent phase. Then, a DLP optimization model was formulated to determine the optimal production strategies. The output of the model represents the amount of optimal in-house and outsourcing production, any necessary capacity extensions and the backordered quantities for each product in every period of the overall planning horizon. Our findings suggest that the proposed integrated ML-based predictive approach and the DLP optimization model can be a valuable resource for decision-makers to choose their strategies.

Undoubtedly, the present paper was a case study with specific configurations. Future work could expand the research applying this framework on a wider variety of manufacturing systems containing more diverse machinery and complex production configurations. Moreover, another area for the development of ideas could be the utilization of more advanced machine learning models such as ensemble methods to improve the accuracy of failure prediction. Furthermore, selection of the ML method by cost-oriented analysis is a new direction in the existing framework. It would be helpful for decision makers to analyze different cost factors such as the cost of maintenance against the cost of production in details. Finally, additional variables such as production limitations or maintenance schedules could be incorporated into the current framework to improve the robustness of the developed predictive model.

However, we plan to expand the model to include elements of the broader supply chain. Considering factors like inventory management, supplier reliability and logistics would allow production planning to be fully synchronized with these external factors. If production planning were synchronized with external factors, a more comprehensive and adaptive system could be achieved.

This research focused on another example of an integrated failure prediction and production planning framework. We believe that if the scope of other supply chain factors expanded, this study would contribute to the development of mechanisms for supply chain systems to possess self-optimization for uncertain and complex conditions in the industrial settings.

REFERENCES

[1] *Mohamed Najid, N., Selsouli Marouane, A., & Abdelmoula, M. (2010). An integrated production and maintenance planning model with time windows and shortage cost. International Journal of Production Research, 19. https://doi.org/10.1080/002075410036203861.*

[2] *Fitouhi, M. C., & Nourelfath, M. (2012). Integrating noncyclical preventive maintenance scheduling and production planning for a single machine. International Journal of Production Economics, 136(2), 344–351. https://doi.org/10.1016/j.ijpe.2011.12.021*

[3] *Sharma, J., Mittal, M. L., & Soni, G. (2024). Condition-based maintenance using machine learning and role of interpretability: a review. In International Journal of System Assurance Engineering and Management (Vol. 15, Issue 4, pp. 1345–1360). Springer. https://doi.org/10.1007/s13198-022-01843-7*

[4] *Shahin, M., Chen, F. F., Hosseinzadeh, A., & Zand, N. (2023). Using Machine Learning and Deep Learning Algorithms for Downtime Minimization in Manufacturing Systems: An Early Failure Detection Diagnostic Service. https://doi.org/10.21203/rs.3.rs-2895149/v1*

[5] *Dangut, M. D., Skaf, Z., & Jennions, I. K. (2021). An integrated machine learning model for aircraft components rare failure prognostics with log-based dataset. ISA Transactions, 113, 127–139. https://doi.org/10.1016/j.isatra.2020.05.001*

[6] *Lee, J., & Mitici, M. (2023). Deep reinforcement learning for predictive aircraft maintenance using probabilistic Remaining-Useful-Life prognostics. Reliability Engineering and System Safety, 230. https://doi.org/10.1016/j.ress.2022.108908*

[7] *Gour, L., & Waoo, A. A (2023). HARD DISK DRIVE FAILURE PREDICTION IN THE DATA CENTER USING ENSEMBLE LEARNING WITH DEEP NEURAL NETWORK MODEL. Materials Today: Proceedings, 58(1). https://doi.org/10.1016/j.matpr.2021.03.229*

[8] *Arena, S., Manca, G., Murru, S., Orrù, P. F., Perna, R., & Reforgiato Recupero, D. (2022). Data Science Application for Failure Data Management and Failure Prediction in the Oil and Gas Industry: A Case Study. Applied Sciences (Switzerland), 12(20). https://doi.org/10.3390/app122010617*

[9] *Zhai, S., Gehring, B., & Reinhart, G. (2021). Enabling predictive maintenance integrated production scheduling by operation-specific health prognostics with generative deep learning. Journal of Manufacturing Systems, 61, 830–855. https://doi.org/10.1016/j.jmsy.2021.02.006*

[10] *Hulbert, S., Mollan, C., & Pandey V. (2022). Fault diagnosis and prediction in automotive systems with real-time data using machine learning. SAE Technical Paper. 2022-01-0217. https://doi.org/10.4271/2022-01-0217*

[11] *Cassady, C. R., & Kutanoglu, E. (2003). Minimizing job tardiness using integrated preventive maintenance planning and production scheduling. IIE Transactions (Institute of Industrial Engineers), 35(6), 503–513. https://doi.org/10.1080/07408170304416*

[12] *Sortrakul, N., Nachtmann, H. L., & Cassady, C. R. (2005). Genetic algorithms for integrated preventive maintenance planning and production scheduling for a single machine. Computers in Industry, 56(2), 161–168. https://doi.org/10.1016/j.compind.2004.06.005*

[13] *Aghezzaf, E. H., Jamali, M. A., & Ait-Kadi, D. (2007). An integrated production and preventive maintenance planning model. European Journal of Operational Research, 181(2), 679–685. https://doi.org/10.1016/j.ejor.2006.06.032*

[14] *Sobaszek, Ł., Gola, A., & Świć, A. (2020). Time-based machine failure prediction in multi-machine manufacturing systems. Eksploatacja i Niezawodnosc, 22(1), 52–62. https://doi.org/10.17531/ein.2020.1.7*

[15] *Zonta, T., da Costa, C. A., Zeiser, F. A., de Oliveira Ramos, G., Kunst, R., & da Rosa Righi, R. (2022). A predictive maintenance model for optimizing production schedule using deep neural networks. Journal of Manufacturing Systems, 62, 450–462. https://doi.org/10.1016/j.jmsy.2021.12.013*

[16] *Leukel, J., González, J., & Riekert, M. (2023). Machine learning-based failure prediction in industrial maintenance: improving performance by sliding window selection. International Journal of Quality and Reliability Management, 40(6), 1449–1462. https://doi.org/10.1108/IJQRM-12-2021-0439*

[17] *Sengottaiyan, N., Vijayakumar, J., Kumar, H. S., Kalyanasundaram, P., & Markkandeyan, S.*

(2022). Maximize the Production Process by Using a Novel Hybrid Model to Predict the Failure of Machine. Proceedings of the 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems, ICSES 2022. https://doi.org/10.1109/ICSES55317.2022.9914172

[18] *Nasser, A., & Al-Khazraji, H. (2022). A hybrid of convolutional neural network and long short-term memory network approach to predictive maintenance. International Journal of Electrical and Computer Engineering, 12(1), 721–730. https://doi.org/10.11591/ijece.v12i1.pp721-730*

[19] *Dehghan Shoorkand, H., Nourelfath, M., & Hajji, A. (2023). A deep learning approach for integrated production planning and predictive maintenance. International Journal of Production Research, 61(23), 7972–7991. https://doi.org/10.1080/00207543.2022.2162618*

[20] *Tortora, A. M. R., Veneroso, C. R., Di Pasquale, V., Riemma, S., & Iannone, R. (2024). Machine Learning for failure prediction: A cost-oriented model selection. Procedia Computer Science, 232, 3195–3205. https://doi.org/10.1016/j.procs.2024.02.135*

[21] *Pinciroli Vago, N. O., Forbicini, F., & Fraternali, P. (2024). Predicting Machine Failures from Multivariate Time Series: An Industrial Case Study. Machines, 12(6). https://doi.org/10.3390/machines12060357*

[22] *Dehghan Shoorkand, H., Nourelfath, M., & Hajji, A. (2024). A hybrid CNN-LSTM model for joint optimization of production and imperfect predictive maintenance planning. Reliability Engineering and System Safety, 241. https://doi.org/10.1016/j.ress.2023.109707*

[23] *Aghezzaf, E. H., & Najid, N. M. (2008). Integrated production planning and preventive maintenance in deteriorating production systems. Information Sciences, 178(17), 3382–3392. https://doi.org/10.1016/j.ins.2008.05.007*

[24] *Alimian, M., Saidi-Mehrabad, M., & Jabbarzadeh, A. (2019). A robust integrated production and preventive maintenance planning model for multi-state systems with uncertain demand and common cause failures. Journal of Manufacturing Systems, 50, 263–277. https://doi.org/10.1016/j.jmsy.2018.12.001*

[25] *Guerroum, M., Zegrari, M., Masmoudi, M., Berquedich, M., & Elmahjoub, A. A. (2022). Machine Learning Technics for Remaining useful Life Prediction using Diagnosis Data: a Case Study of a Jaw Crusher. International Journal of Emerging Technology and Advanced Engineering, 12(10), 122–135. https://doi.org/10.46338/ijetae1022_14*

[26] *Roosefert Mohan, T., Preetha Roselyn, J., Annie Uthra, R., Devaraj, D., & Umachandran, K. (2021). Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. Computers and Industrial Engineering, 157. https://doi.org/10.1016/j.cie.2021.107267*

[27] *Wang, H., Liao, H., & Ma, X. (2021). Remaining Useful Life Prediction Considering Joint Dependency of Degradation Rate and Variation on Time-Varying Operating Conditions. IEEE Transactions on Reliability, 70(2), 761–774. https://doi.org/10.1109/TR.2020.3002262*

[28] *Bampoula, X., Siaterlis, G., Nikolakis, N., & Alexopoulos, K. (2021). A deep learning model for predictive maintenance in cyber-physical production systems using LSTM autoencoders. Sensors (Switzerland), 21(3), 1–14. https://doi.org/10.3390/s21030972*

[29] *Kareem, B., & Jewo, A. O. (2015). Development of a model for failure prediction on critical equipment in the petrochemical industry. Engineering Failure Analysis, 56, 338–347. https://doi.org/10.1016/j.engfailanal.2015.01.006*

[30] *Singh, S., Agarwal, T., Kumar, G., & Yadav, O. M. (2019). Predicting the remaining useful life of ball bearing under dynamic loading using supervised learning. 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Macao, China, 1119–1123. https://doi.org/10.1109/IEEM44572.2019.8978649*

[31] *Ozkat, E. C., Bektas, O., Nielsen, M. J., & la Cour-Harbo, A. (2023). A data-driven predictive maintenance model to estimate RUL in a multi-rotor UAS. International Journal of Micro Air Vehicles, 15. https://doi.org/10.1177/17568293221150171*

[32] *Schreiber, M., Vernickel, K., Richter, C., & Reinhart, G. (2019). Integrated production and maintenance planning in cyber-physical production systems. Procedia CIRP, 79, 534–539. https://doi.org/10.1016/j.procir.2019.02.095*

[33] *Yalaoui, A., Chaabi, K., & Yalaoui, F. (2014). Integrated production planning and preventive maintenance in deteriorating production systems. Information Sciences, 278, 841–861. https://doi.org/10.1016/j.ins.2014.03.097*

[34] *Lu, F., Wu, J., Huang, J., & Qiu, X. (2019). Aircraft engine degradation prognostics based on logistic regression and novel OS-ELM algorithm. Aerospace Science and Technology, 84, 661–671. https://doi.org/10.1016/j.ast.2018.09.044*

[35] *Aghamohammadghasem, M., Azucena, J., Liao, H., Zhang, S., & Nachtmann, H. (2023). Preventive Maintenance Planning for an Inland Waterway Transportation System Using Deep Reinforcement Learning. In IIE Annual Conference. Proceedings (pp. 1-6). Institute of Industrial and Systems Engineers (IISE). https://www.researchgate.net/publication/374229183*

[36] *Jabeur, S. Ben, Gharib, C., Mefteh-Wali, S., & Arfi, W. Ben. (2021). CatBoost model and artificial intelligence techniques for corporate failure prediction. Technological Forecasting and Social Change, 166. https://doi.org/10.1016/j.techfore.2021.120658*

[37] *Bagheri, F., Demartini, M., Arezza, A., Tonelli, F., Pacella, M., & Papadia, G. (2022). An Agent-Based Approach for Make-To-Order Master Production Scheduling. Processes, 10(5). https://doi.org/10.3390/pr10050921*

[38] *Vieira, G. E. (n.d.). Chapter 7 A PRACTICAL VIEW OF THE COMPLEXITY IN DEVELOPING MASTER PRODUCTION SCHEDULES: FUNDAMENTALS, EXAMPLES, AND IMPLEMENTATION.*

[39] *Lauer, T., Legner, S., & Henke, M. (2019). Application of machine learning on plan instability in master production planning of a semiconductor supply chain. IFAC-PapersOnLine, 52(13), 1248–1253. https://doi.org/10.1016/j.ifacol.2019.11.369*