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Predictive Maintenance Planning Using a Hybrid ARIMA-ANN Model

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Abstract
Predicting machine faults is crucial for maintaining operational efficiency in industrial settings, minimizing unplanned downtime, and ensuring customer satisfaction. Fault prediction helps identify faults and create maintenance schedules. Maintenance planning involves strategically scheduling activities to ensure the continuous operational efficiency of systems. This study focuses on reducing unplanned downtime in a food company by developing a predictive maintenance plan through machine fault prediction. Artificial Neural Networks (ANNs) are excellent in handling non-linear models, while the ARIMA model is adequate for linear models. However, real-world data often contains linear and non-linear elements, requiring hybrid models for improved accuracy. This study employs ARIMA, ANNs, and a Hybrid ARIMA-ANN model. The dataset is individually modeled using each approach. Using a 3-month machine fault dataset, predictive values for machine fault times are generated and statistically evaluated using metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The findings indicate that the hybrid model outperforms both ARIMA and ANN models. The food company can significantly reduce unplanned downtime and ensure operational efficiency using a hybrid model. Predictive maintenance planning can help the food company save costs and maintain a competitive edge in the market.

1. Introduction

Predicting faults is crucial for industrial maintenance strategies to prevent system failures and minimize unplanned downtime. Accurate predictions of future failures are necessary for designing timely maintenance activities [1]. To remain competitive and satisfy customers, it is essential to eliminate system downtimes and unforeseen causes leading to them.

Many businesses perform breakdown maintenance randomly after the occurrence of a fault, resulting in significant time loss during repairs [2]. In several sectors, multiple machines work together in a cycle to produce final products. Therefore, the interdependency of operations is crucial to prevent system disruptions. Unplanned maintenance could cause damage to different machines or parts, leading to an imbalance in the system, accumulation of intermediate products, delays in work, and idle labor, resulting in waste. Poor planning damages a company's reputation and leads to financial losses due to untimely product deliveries.

Predicting faults and performing maintenance accordingly significantly mitigates hazardous situations, accidents, injuries, material damage, and extensive time loss. It also ensures that machines operate correctly, smoothly, and in a controlled manner [3]. Data processing, analyzing data, and generating meaningful insights for future predictions have become increasingly important [4]. Mathematical and statistical methods were initially used in prediction studies [5]–[8]. However, traditional methods have become inadequate with the increasing volume of data, variables, and uncertainties. Machine learning algorithms that can self-learn and adapt have been employed in prediction

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studies [9]–[13]. Machine learning algorithms find applications in various fields, such as machine maintenance and repair planning, production and supply chain planning, financial calculations, and more in manufacturing.

Maintenance planning aims to calculate the occurrence time of a fault, take quick preventive measures before a fault occurs, and prevent unnecessary maintenance. Traditional maintenance planning methods are still used in businesses [14], [15]. Unnecessary maintenance can lead to the replacement of parts that could have lasted longer without a system failure, halting production for excessive maintenance and unnecessary labor and spare part usage. The goal is to optimize the duration of maintenance work, perform maintenance before faults occur, and prevent unnecessary maintenance.

Existing prediction studies in the literature use time series models and machine learning algorithms [16]–[18]. While predictions made using time series provide good results in linear models, predictions made using machine learning provide good results for non-linear models. A hybrid prediction model using the ARIMA-ANN method for fault prediction has yet to be found in the literature. Real-life data is a mix of linear and non-linear data, making it challenging to model and predict. Hence, it is predicted that the results of prediction studies using hybrid models will be better than those using linear and non-linear models.

The primary objective of this study is to eliminate unplanned downtimes and create a predictive maintenance plan to ensure that the system operates smoothly and is ready for production at any time. To achieve this, machine fault times were predicted by modeling the cumulative fault data obtained from a food production company's dryer, which causes the most interruptions in production, using ARIMA, ANN, and ARIMA-ANN hybrid models. The results obtained were compared using performance metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

The rest of the paper is organized as follows: Section 2 presents a comprehensive literature review. Section 3 provides information on maintenance planning. In Section 4, ARIMA, ANN, and the hybrid model are introduced, respectively. In Section 5, an experimental study is carried out to verify the forecasting performance of the proposed models. In the last section, conclusions and recommendations are presented.

2. Literature Review

Predictive maintenance is a crucial strategy in industrial settings. It aims to anticipate and prevent equipment failures before they occur. This approach helps minimize unplanned downtimes, improve operational efficiency, and reduce maintenance costs. The literature on predictive maintenance can be broadly categorized into three main approaches: statistical methods, machine learning techniques, and hybrid models.

Statistical methods, particularly time series analysis, have been extensively used in predictive maintenance. Time series models, such as ARIMA, effectively handle linear data and forecast future failures based on historical data trends. For instance, Aktaş and Aydın [19] employed time series analysis to predict production efficiency in machining operations, demonstrating the capability of these methods to provide accurate forecasts in linear systems. Similarly, ARIMA models have been utilized for error detection and predictive maintenance forecasts [6], [7]. However, compared to machine learning methods, ARIMA models are less flexible and often less accurate in capturing complex data patterns [20], [21].

With the continuing development of big data, AI, and IoT technologies, which are driving forces of Industry 4.0, machine learning techniques have gained prominence in predictive maintenance [22]. These techniques have been applied to various aspects, such as supervised classification, regression in high-dimensional data, reinforcement learning for system modeling, and unsupervised learning problems. Machine learning algorithms, such as ANN, have the ability to learn complex patterns and relationships within data, making them suitable for predicting equipment failures in non-linear systems. Zuo et al. [23] utilized a spiking neural network (SNN) for bearing fault diagnosis in manufacturing settings, highlighting the effectiveness of machine learning in detecting and predicting faults. Similarly, Sampaio et al. [24] applied ANN to predict motor failure times, further validating the robustness of these techniques in industrial applications. Ben Ali et al. [25] and Mahamad et al. [26] demonstrated the efficacy of ANN models in bearing fault diagnosis and remaining functional life prediction, respectively, showcasing significant improvements over traditional approaches.

Recent studies have also demonstrated the application of more advanced machine learning models. Zhang et al. [27] investigated the development of models using temporally dependent sensor data for NASA's aircraft engine performance monitoring and useful life expectancy estimation. They employed a Long Short-Term Memory (LSTM) based model, which outperformed other machine learning techniques such as Support Vector Regression (SVR), Multilayer Perceptron (MLP), and Deep Convolutional Neural Networks (DCNN) in predicting useful life. Similarly, Lee et al. [28] used SVR and ANN models to predict spindle motor and cutting machine wear and malfunctions, achieving successful results. Hybrid models combine the strengths of statistical methods and machine learning techniques to address the limitations of each approach when used in isolation. These models are beneficial for handling real-life data that often exhibit both linear and non-linear characteristics. Paithankar and Chatterjee [29] proposed a hybrid data-driven method using a neural network and genetic algorithm to forecast failure time. Similarly, Yang et al. [30] developed a hybrid prediction model based on a state observer and a hidden Markov model (HMM) for control systems. Xu et al. [31] introduced a hybrid SARIMA-SVR model to predict statistical indicators in the aviation industry.

Predictive maintenance has been applied across various industrial sectors. In the manufacturing industry, predictive models are used to diagnose faults in critical components such as bearings and motors, ensuring continuous and efficient production processes. In the aviation industry, Çelikmıh et al. [32] utilized machine learning techniques to predict aircraft maintenance periods and fault counts, enhancing the reliability and safety of aircraft operations. Dindarloo et al. [33] applied SARIMA (Seasonal ARIMA) to predict the time between failures for heavy machinery, demonstrating the versatility of statistical models in different industrial contexts. The food industry presents unique maintenance and fault prediction challenges due to the high variability in production processes and the critical need to ensure product safety and quality. A few studies have explored the application of machine learning techniques in this sector to enhance predictive maintenance strategies. Liu [34] introduced a fault diagnosis approach for food machinery equipment based on neural networks. In another study, Setiawan et al. [35] performed multiple linear regression analysis to predict machine breakdowns in the food seasoning industry.

Given the advancements in production and technology, accurately estimating the remaining useful life (RUL) of machinery has become crucial for maintaining machine condition monitoring, enhancing productivity, ensuring reliability, and promoting safety [12], [36]. Various theoretical and practical methodologies have been proposed, including sophisticated deep learning models that consolidate multiple facets into a single application. The necessity for real-time processing of intricate data streams has been underscored across different application scenarios. Rivera et al. [37] investigated production system errors through the lens of anomaly detection, highlighting the pivotal role of data quality and expert knowledge in augmenting predictive accuracy.

The evolution of predictive maintenance has seen a transition from traditional statistical methods to advanced machine learning techniques and hybrid models. Each approach offers unique advantages and, when appropriately applied, can significantly enhance the reliability and efficiency of maintenance operations. Integrating these methods into a cohesive predictive maintenance strategy promises to improve industrial productivity further and reduce operational costs.

provides a summary of the reviewed studies in terms of focus, methodology, and field of application.

3. Maintenance Planning

Maintenance planning is a critical aspect of ensuring the smooth and efficient operation of industrial and service sectors. It encompasses the systematic arrangement of activities to maintain equipment functionality and minimize downtime. Effective maintenance planning is essential for businesses striving for uninterrupted production and service delivery [38]. Figure 1 illustrates various categories of maintenance planning [39].

Planned maintenance is the maintenance performed to prevent failures before they occur. It ensures that machines and equipment can operate smoothly at any given time. The objectives of planned maintenance include extending the life of machines and equipment, improving performance, reducing downtime and costs associated with breakdowns, keeping equipment ready for production at all times, minimizing damage in case of failures, reducing maintenance and repair expenses, decreasing the need for spare machines, creating a safe working environment for workers, and minimizing expenses arising from potential accidents [40]. Planned maintenance is often divided into preventive maintenance and corrective maintenance.

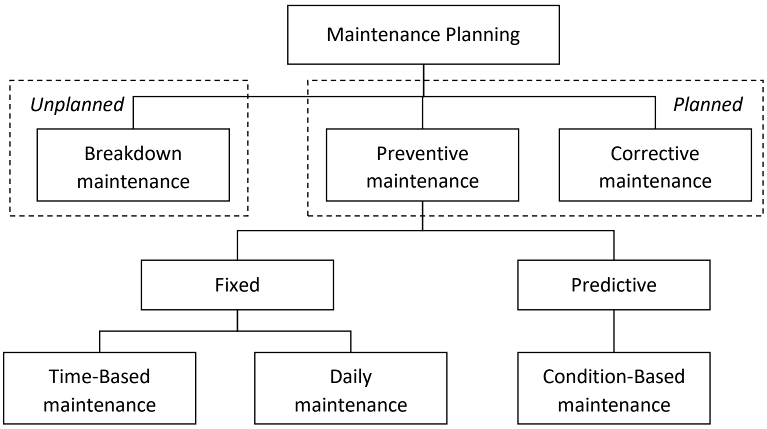

Figure 1. Types of maintenance

Table 1. A summary of the related literature

Study	**Focus**	**Approach**	**Application Area**
Zuo et al. [23]	Bearing fault diagnosis	SNN	Manufacturing
Çelikmıh et al. [32]	Prediction of aircraft maintenance periods and fault counts	Machine Learning	Aircraft
Sampaio et al. [24]	Motor failure time prediction	ANN	Engine
Aktaş and Aydın [19]	Production efficiency prediction	Time Series methods	Machining
Ben Ali et al. [25]	Bearing fault diagnosis	ANN	Manufacturing
Mahamad et al. [26]	Remaining useful life prediction of machines	ANN	Manufacturing
Baptista et al. [6]	Maintenance plan for an aircraft part	ARMA	Aircraft
Dindarloo [33]	The time between failure prediction	SARIMA	Heavy Machinery
Fernandes et al. [7]	Fault detection for predictive maintenance	ARIMA	Metallurgy
Medeiros et al. [41]	Failure prediction	Machine Learning Algorithms	Insulators
Kang et al. [42]	Anomaly perception and failure prediction	SVR	High-speed automatic train
Paithankar and Chatterjee [29]	Failure time prediction	Hybrid Neuro Genetic Algorithm	Mining machinery
Vargas et al. [36]	Fault prediction	Hybrid Machine Learning Algorithms	Automated teller machines (ATMs)

Preventive maintenance is a type of maintenance that businesses have recently begun to adopt. This method aims to prevent failures resulting from faults in machines and facilities. Serious research and development efforts are required for preventive maintenance. Preventive maintenance includes daily routine actions such as cleaning, refueling, inspection to prevent deterioration, periodic examination, and equipment diagnosis. These actions maintain the "health" of the equipment and prevent failures.

Predictive Maintenance predicts the life of a significant part through monitoring and diagnosis [43], [44]. Therefore, maintenance costs and breakdown losses are lower with this method compared to others. One type of predictive maintenance is Condition-Based Maintenance (CBM) [45]. This maintenance type uses condition diagnostic technology (CDT) to monitor the equipment's condition online.

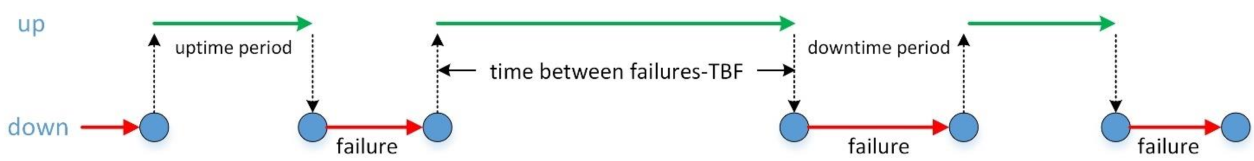

Figure 2. Measurement of time between failures [46]

In enterprise operations, thermal cameras, sensors, measurement devices, and similar technologies play a crucial role in monitoring specific areas of machinery and facilities at regular intervals [45], [47]. These observations are meticulously recorded to support proactive maintenance strategies, known as predictive maintenance. This approach focuses on swiftly detecting any deviations in system performance to intervene promptly and prevent potential malfunctions. Techniques employed in this maintenance paradigm include oil analysis, thermal imaging for temperature analysis, and other sensor-based assessments.

Predictive maintenance strategies typically involve three key stages. The first stage is detection, promptly identifying deviations in the machinery's operational conditions. Subsequently, the analysis and diagnosis phase examines the machine's characteristics to determine the underlying causes of the observed changes. Finally, the corrective phase involves implementing necessary repairs, maintenance, and replacements to rectify identified issues and ensure optimal operational efficiency. Predictive maintenance relies on accurate predictions of future failures to design timely maintenance activities. Approaches to failure prediction analyze current and past data representing system conditions, events, and operations [1]. A critical parameter in predicting failure time is the time between failures (TBF). Figure 2 illustrates how this duration is measured.

4. Methodology

4.1. The Autoregressive Integrated Moving Average

The autoregressive integrated moving average (ARIMA) model, introduced by Box and Jenkins [48], stands as a cornerstone in time series forecasting. ARIMA models capture the inherent relationships (autocorrelations) between past and present values within the data. A fundamental assumption of The ARIMA (p, d, q) model is that the underlying data series is stationary, meaning its statistical properties (mean, variance) remain constant over time and exhibit no specific trend.

The ARIMA model expresses the future value (Y_t) of a variable as a linear combination of two key elements: (i) past observations, represented by the terms $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$, where p signifies the order of auto-regression, (ii) past errors, captured by the terms $\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$, where ε_t represents the error term at time t, and q denotes the order of moving average. This relationship can be mathematically expressed as:

$$Y_t = c + \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \tag{1}$$

Y_t: Represents the value of the variable at time t.

c: Constant term.

ϕ_i: Coefficients associated with the autoregressive (AR) component, quantifying the influence of past observations (Y_{t-i}) on the future value.

ε_t: White noise error term at time t.

θ_i: Coefficients associated with the moving average (MA) component, reflecting the impact of past errors (ε_{t-i}) on the future value.

The ARIMA model leverages the power of past observations and error terms to provide a robust and data-driven approach to forecasting future trends in time series data.

4.2. Artificial Neural Network

ANNs are a class of machine learning models inspired by the neural networks in the human brain. They are designed to recognize patterns and make predictions based on input data. ANNs are composed of interconnected units called neurons, organized into layers. Each neuron calculates a weighted sum of its inputs and passes this sum through an activation function, introducing non-linearity to model complex relationships. The most common activation functions include the sigmoid, tanh, and rectified linear unit. There are many types of ANN, such as multilayer perceptron (MLP), radial basis function (RBF) networks, and recurrent neural networks (RNN) used by researchers in prediction studies [49]–[52].

Although MLP was initially developed to tackle complex classification problems, due to their universal approximation capability, they were soon utilized for nonlinear regression models and subsequently for time series modeling and forecasting. However, the estimation and identification of these models involve sophisticated techniques, making it challenging to determine the correct architecture. These models are often overparametrized, the error functions to be minimized have numerous local minima, and their implementation is frequently difficult [53].

Nonlinear Autoregressive (NAR) Neural Network extends the basic principles of ANNs by incorporating temporal dependencies. NAR networks predict future values of a time series based on its past values. This autoregressive approach uses previous time points as part of its input to forecast future values. Unlike traditional ANNs, NAR networks have input, hidden, and output layers. However, the input layer takes lagged time series values, allowing the model to capture temporal dynamics.

The NAR model, depicted in Figure 3, can be mathematically expressed as:

$$\mathrm{y(t)} = \mathrm{f}\big(\mathrm{y(t-1)}, \mathrm{y(t-2)}, \ldots, \mathrm{y(t-d)}\big) + \varepsilon(t) \quad (2)$$

where y(t) is the value at time *t*, *d* is the time delay parameter, and the *ε(t)* indicates the approximation error at time *t*.

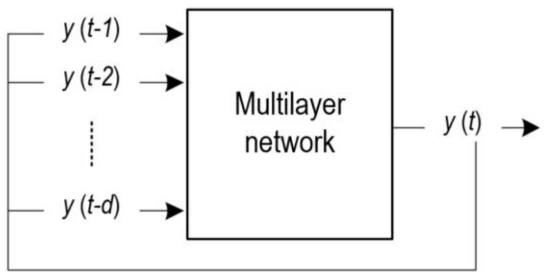

Figure 3. Non-linear autoregressive (NAR) network

4.3. ARIMA-ANN models

In recent years, in the field of time series analysis, hybrid models that use multiple models together have been introduced to improve modeling and forecasting performance. Especially with the advancement of machine learning, numerous hybrid models that combine classical statistical methods and machine learning techniques have been developed [54], [55].

One of the most important classes of hybrid models is the ARIMA-ANN hybrid model class. The strong performance of the ARIMA model for linear time series and the success of the ANN model for nonlinear time series have led researchers to create hybrid models that incorporate both models. The fact that real-world time series often contain both linear and nonlinear characteristics is one of the main reasons for the high modeling and forecasting performance of ARIMA-ANN hybrid models [56]. In studies, time series is approached in various ways, such as the sum [18], product [57], or a nonlinear function of the values obtained from the linear series and the actual series [58] of linear and nonlinear series [56].

Zhang [18] introduced the first ARIMA-ANN model in the literature, considering the time series as the sum of linear and nonlinear series. In the model proposed by Khashei and Bijari [58], the series is not segmented into linear or nonlinear components. Instead, it is viewed as a nonlinear function of observations and errors. On the other hand, Babu and Reddy [59] separate the time series into linear and nonlinear series by passing it through a moving average filter.

4.4. Proposed Hybrid Model

The ARIMA-ANN model, first introduced by Zhang [18], is considered a highly effective tool for time series analysis. This model allows for the decomposition of time series into linear and nonlinear components, enabling separate modeling of each component.

$$Y_t = L_t + N_t \quad (3)$$

where, Y_t represents the actual observations of the time series, L_t denotes the linear trends captured by the ARIMA models. It uses autoregressive and moving average concepts based on past values to forecast future values. N_t represents the nonlinear trends and complexities of the series captured by ANNs. ANNs utilize their learning capability to model these trends. As shown in Figure 4, the proposed ARIMA-ANN hybrid model consists of four fundamental steps.

Step 1. The time series is modeled with ARIMA to obtain the initial forecast value. For this purpose, seasonality and trend analysis are conducted, and the stationarity of the series is checked. If it is non-stationary, it is transformed into a stationary form, and ACF-PACF plots are drawn. The most suitable ARIMA (p, d, q) model for the series is computed with the assistance of software, and the initial predicted value $\hat{x}(i)$ can be calculated.

Step 2. The residual values $y(i)$ are computed. Let the time series be denoted by $x(i)$, and the initial forecast value be denoted by $\hat{x}(i)$. The residual value is calculated by taking the difference between the forecasted value and the actual data.

$$y(i) = \hat{x}(i) - x(i) \tag{4}$$

Step 3. Raw data is utilized to train the ANN network. The architecture of the ANN model is determined. The number of hidden layers, neurons per layer, and activation functions can be adjusted within the chosen network type. The Levenberg-Marquardt algorithm or other available training functions optimize the network's weights and biases. The designed ANN architecture using the residual values is trained as the input data. This process continues until a specified number of epochs (iterations) is reached or until a certain error threshold is achieved.

Step 4. The final predicted value $x_t^*(i)$ of the combination model is obtained through the relationship between the new residuals $\hat{y_t}(i)$ and the initially predicted values $\hat{x}(i)$. The predicted values of the hybrid model are computed by taking the difference between the forecast value obtained with the ARIMA model and the forecast value obtained with the ANN model.

$$x_t^*(i) = \hat{x}(i) - \hat{y_t}(i) \tag{5}$$

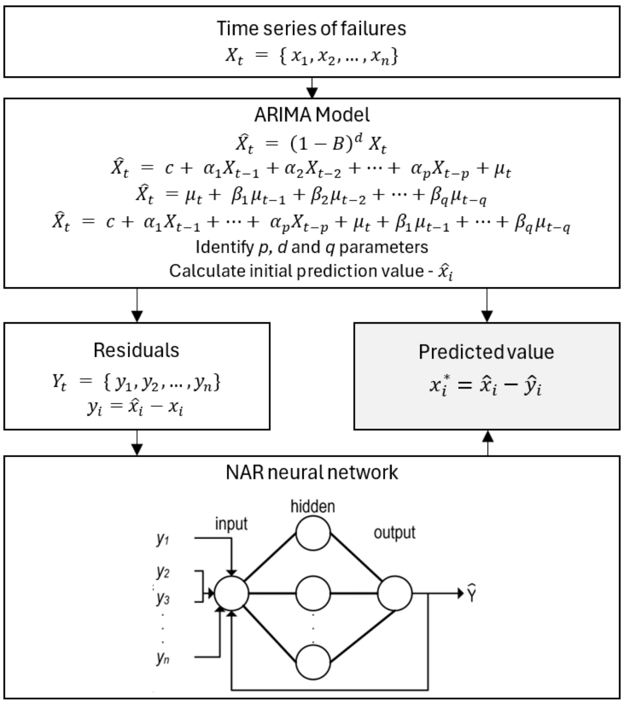

Figure 4. Flowchart of the ARIMA-ANN model

5. Case Study

In this study, predictions of machine failure time were derived utilizing the hybrid methodology described in the previous section. The linear component of the model was estimated using the ARIMA model, while the non-linear component was addressed by applying the NAR neural network method. The hybrid model was constructed by integrating these two models. Subsequently, the results of the hybrid model were compared with the prediction performances of the ARIMA and NAR neural network (NAR-NN) models. Time series plots of the predicted and actual values are presented in this section.

5.1. Background and Dataset

A case study was conducted at a facility engaged in pasta production to evaluate the proposed method. The facility operates three shifts per day. Data containing the day and time of malfunctions occurring on the production line were obtained from the company and utilized for prediction purposes. Upon examining the data, it was decided to focus on addressing malfunctions explicitly occurring in the drying machine, which constitutes a critical component causing significant disruptions to production and playing a vital role in daily operations. Should the drying line fail, the entire production process stops. Management aims to effectively anticipate the downtime of the machine, enabling the implementation of suitable maintenance scheduling activities to prevent malfunctions.

The times between failures and cumulative times for a total of 50 failures that occurred in the drying line are presented in Table A1 (see Appendix), along with a time series plot of the cumulative data shown in Figure 5. For prediction purposes, the cumulative downtime data were utilized, with the last 8 out of the 50 cumulative failure data points reserved as test data, while the remaining data points were used for training.

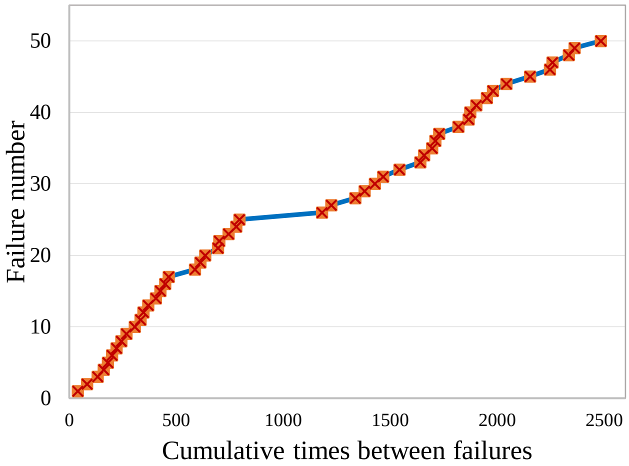

Figure 5. The time series of machine failure data

5.2. Performance Metrics

To quantitatively assess the deterministic predictions obtained from the ARIMA, ANN, and hybrid ARIMA-ANN models, three performance metrics were employed: Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). The detailed mathematical expressions for these metrics are listed below:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}{n}} \tag{7}$$

where, y_t is the observed value, $\hat{y}_t$ is the predicted value, n is the total number of observations.

5.3. Analysis, Results and Discussions

In this section, the steps of the proposed model are applied to the data of the time between drying line failures. Then, a series of experimental studies are carried out to validate the effectiveness of the proposed model. The case study data is analyzed using ARIMA, NAR-NN, linear regression (LR), and Winters' methods and compared with the results of the hybrid model.

ACF and PACF graphs were used to assess the stationarity of the time series. The ACF graph indicated non-stationarity, as the autocorrelation values exceeded the boundary values. Therefore, differencing was considered necessary to achieve stationarity (Figure 5). The PACF graph revealed that the first lag had the highest partial autocorrelation value, suggesting that differencing of order 1 (d=1) should be applied to the series (Figure 6).

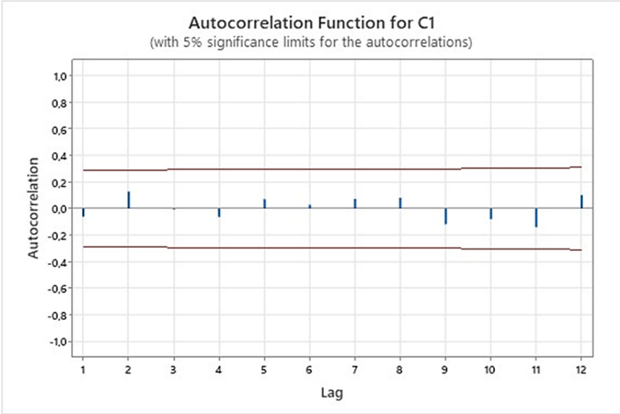

Figure 5. ACF graph of cumulative times between failures (TBFs) data

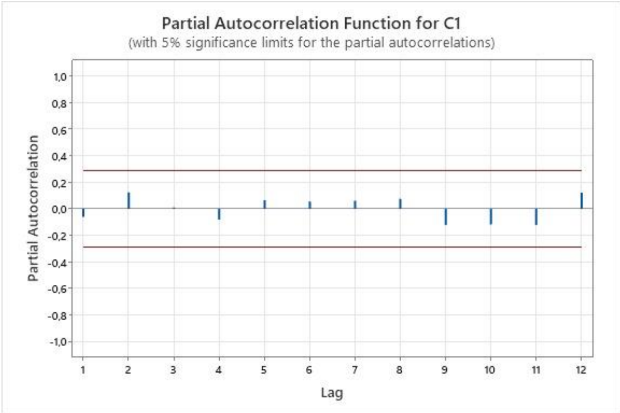

Figure *6*. PACF graph of cumulative times between failures (TBFs) data

Since only the first lag was significant in the ACF graph, it was inferred that q=1. Therefore, the ARIMA model would contain a moving average component with q=1. Based on the analysis, the differencing of order 1 should be performed to achieve stationarity, and an ARIMA(0,1,1) model should be the most appropriate for the given data set. The predicted value of the ARIMA model for training data is plotted in Figure 7.

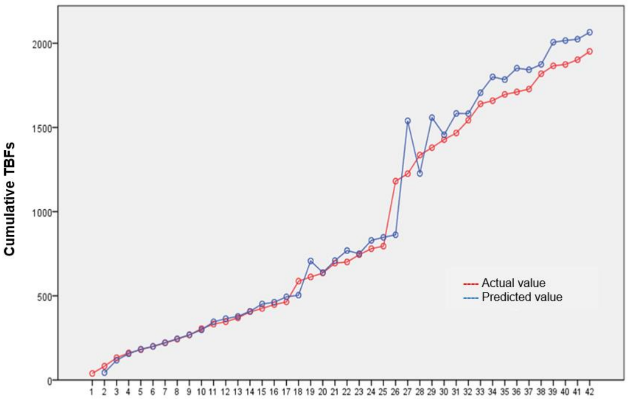

Figure 7. Failure prediction with ARIMA (0,1,1) model

In the case study, a multilayer NAR-NN was utilized for fault time prediction, characterized by its ability to model temporal dependencies through an autoregressive approach. This network, implemented in MATLAB, comprised one input layer, ten hidden layers, and one output layer. The choice of a lag of 1 allowed the network to use the immediate past value for making predictions. The hidden layers, numbering ten, were selected to provide sufficient depth for capturing complex patterns in the data, balancing model complexity with computational efficiency. Figure 8 shows the architecture of the NAR neural network.

The network employed the Levenberg-Marquardt algorithm for training, chosen for its speed and accuracy in converging to optimal solutions compared to other algorithms. The training was conducted over 1000 epochs to ensure thorough learning from the data, minimizing risks of underfitting. The network performance was evaluated using the Mean Squared Error (MSE), a standard metric for regression tasks that effectively quantifies prediction accuracy. The activation function used in the hidden layers was the hyperbolic tangent sigmoid (tansig), which was preferred for its strong gradients and reduced risk of neuron saturation, facilitating stable and effective learning. Combining these parameters and methods ensured a robust model capable of accurately predicting fault times.

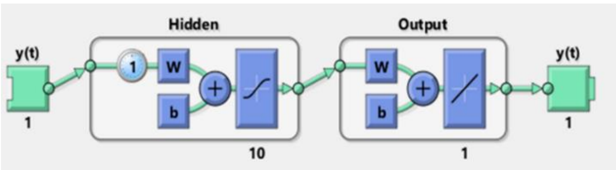

Figure 8. The architecture of the NAR-NN

The residual values, $y(i)$, are obtained by finding the difference between the ARIMA model's estimated value and the actual data using Eq. (4), and then they are used in the estimation process of the NAR-NN model. To build the neural network model, 42 instances of fault data were used from the dataset, while eight cases were kept aside for testing. Based on the dataset, the model accurately calculates the predicted values for eight residual values. The predicted residual, $\widehat{y}_t(i)$, values for test data get presented in Table 2. To obtain the failure prediction results, $(x_t^*(i))$ for the hybrid approach, Eq. (5) is used. The failure prediction values of the hybrid model are also provided in Table 2.

Table 2. Validation of the hybrid method with test data

Failure no	Observed values $y_t(i)$	ARIMA $\hat{x}(i)$	Residual values $y(i)$	Predicted residual values $\widehat{y}_t(i)$	Predicted values $x_t^*(i)$
43	1980	2125.5	145.5	120.1	2005.4
44	2043	2392.5	349.5	324.7	2067.8
45	2153	2693.1	540.1	522.0	2171.1
46	2246	3031.4	785.4	777.4	2254.0
47	2258	3412.2	1154.2	1163.3	2249.0
48	2335	3840.9	1505.9	1527.3	2313.6
49	2362	4323.4	1961.4	1978.7	2344.7
50	2485	4866.5	2381.5	2404.1	2462.4

Table 3 reveals the statistical results of the test data for the ARIMA, NAR-NN, and hybrid models. The ARIMA model has a MAPE value of 43.375, the NAR-NN model has a MAPE value of 5.117, and the hybrid model has a MAPE value of 0.832. Figure 9 shows the trend of the error rate of the prediction models over time. According to Lewis [60], the MAPE values are classified as follows:

- "Very good" for MAPE below 10%
- "Good" for MAPE between 10% and 20%
- "Acceptable" for MAPE between 20% and 50%
- "Incorrect and faulty" for MAPE above 50%

With this evaluation, we can confidently say that the hybrid and ANN models offer exceptional results, while the ARIMA model's results are unacceptable. Moreover, the hybrid model outperforms the ANN model with its lower MAPE value. Therefore, the hybrid model is the most reliable choice for accurate predictions.

Table 3. Comparison results of the test data

#	Observed values	ARIMA (0,1,1)		NAR-NN		Hybrid Model	
		Model value	Error %	Model value	Error %	Model value	Error %
Out-of-sample							
43	1980	2125.5	0.073	1980.0	0.000	2005.4	0.013
44	2043	2392.5	0.171	2107.4	0.032	2067.8	0.012
45	2153	2693.1	0.251	2159.0	0.003	2171.1	0.008
46	2246	3031.4	0.350	2159.0	0.039	2254.0	0.004
47	2258	3412.2	0.511	2159.0	0.044	2249.0	0.004
48	2335	3840.9	0.645	2159.0	0.075	2313.6	0.009
49	2362	4323.4	0.830	2159.0	0.086	2344.7	0.007
50	2485	4866.5	0.958	2159.0	0.131	2462.4	0.009
MAPE (%) (#43-50)		47.375		5.117		0.832	

Linear Regression and Winters' method are also applied for the machine failure data to verify the proposed method's effectiveness. The results, as summarized in Table 4, demonstrate significant differences in accuracy and error across the methods. Linear regression performed the worst, with a high MAPE of 39.071% and an RMSE of 136.5, indicating poor prediction accuracy. Winters' method showed better performance with a MAPE of 7.829% and an RMSE of 93.30, but still fell short compared to more advanced models. ARIMA improved further, achieving a MAPE of 7.361% and an RMSE of 101.9, reflecting its capability to model time series data more effectively. The NAR-NN demonstrated a significant improvement, with a MAPE of 1.586% and an RMSE of 9.807, indicating its strong ability to capture nonlinear relationships and temporal dependencies. However, the proposed hybrid model outperformed all other methods, achieving the lowest MAPE of 0.384% and an RMSE of 2.167, showcasing the advantages of combining multiple techniques for superior accuracy and minimal prediction errors.

6. Conclusion and Suggestions

The primary objective of this research is to ensure the efficient functioning of a food production company's production line by foreseeing and preventing potential breakdowns through strategic maintenance planning. The focus lies in foreseeing unexpected downtime, conducting predictive studies on machine breakdowns, and scheduling maintenance at optimal intervals. The right timing for scheduling maintenance is crucial in averting unforeseen breakdowns, avoiding unnecessary disruptions in production, and reducing waste.

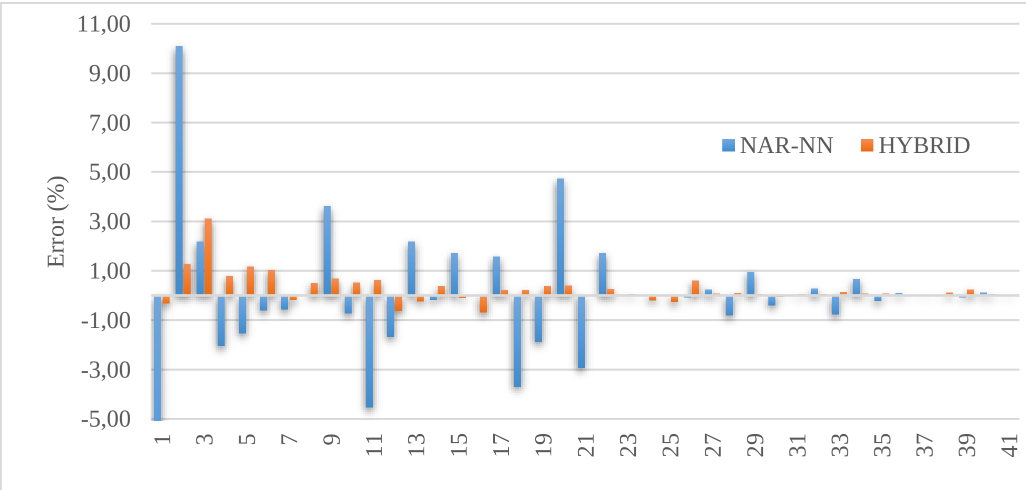

Figure 9. Trends of percentage of forecasting error

Table 4. Comparison of failure prediction results

Data	Methods	MAPE (%)	RMSE
machine failure data	Linear regression	39.071	136.5
	Winters'	7.829	93.30
	ARIMA	7.361	101.9
	NAR-NN	1.586	9.807
	Hybrid model	0.384	2.167

The study proposes a hybrid ARIMA-ANN method that combines time series and machine learning techniques. This hybrid model effectively integrates the strengths of linear and non-linear models to develop a preventive maintenance plan that can anticipate future potential breakdowns. This plan takes proactive measures to prevent breakdowns by scheduling maintenance at the appropriate times. The hybrid model outperforms traditional linear and non-linear models. Below, we have itemized the discussions and findings into industrial gains.

- The proposed hybrid model accurately predicts machine faults, allowing for predictive maintenance planning. This reduces unplanned downtimes and improves overall production efficiency.
- By predicting faults and performing maintenance before failures occur, companies can avoid the high costs associated with emergency repairs, production stoppages, and idle labor.
- The model helps ensure that machinery operates smoothly and reliably, thereby extending the lifespan of equipment and reducing the frequency of maintenance interventions.
- Accurate fault predictions help streamline maintenance schedules, ensuring that maintenance activities are performed at optimal

times, minimizing disruptions to the production process.

This study contributes to the body of knowledge on predictive maintenance by demonstrating the effectiveness of a hybrid ARIMA-ANN model in a real-world industrial setting, specifically within the food industry. Integrating ARIMA and ANN models addresses linear and non-linear data patterns, offering a robust approach to fault prediction. This hybrid methodology can be adapted and applied to other industries and machinery types.

While this study focused on a food production company, the hybrid ARIMA-ANN model we developed for predictive maintenance is highly adaptable and applicable to various industries with similar maintenance challenges. The model combines the strengths of linear and non-linear prediction methods, making it suitable for industries such as manufacturing, automotive, aerospace, and energy sectors that require accurate maintenance planning. It relies on historical fault data and operational parameters, which are common across different industries, and its scalable methodology ensures consistent data collection, preprocessing, and model training for both large-scale production lines and smaller units. The model's parameters can be customized to meet specific maintenance requirements and operational conditions of various sectors.

While the hybrid ARIMA-ANN model showed promising results in predicting machine faults with the available data, it is essential to note that neural networks typically benefit from larger datasets. Increasing the volume of training data can enhance the model's reliability and generalization capabilities. Future studies should collect and utilize as much data as possible to improve prediction accuracy. To further validate the model, future research could implement it across different industries and compare performance metrics, benchmark it against existing industry-specific maintenance tools, and test it with diverse data types and machinery to ensure robustness and adaptability.

Contributions of the authors

Bilal Ervural: Conceptualization, Research Design, Editing, Supervision, Model Development, Manuscript Writing, Review, Final Approval. Gamze Kaynak: Literature Review, Data Collection, Data Analysis, Model Development.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study complies with research and publication ethics.

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Appendix

Table A1. Actual TBFs and cumulative data

Failure No	TBFs (hour)	Cumulative TBFs (hour)	Failure No	TBFs (hour)	Cumulative TBFs (hour)
1	39	39	**26**	386	1181
2	43	82	**27**	44	1225
3	50	132	**28**	111	1336
4	29	161	**29**	44	1380
5	19	180	**30**	48	1428
6	19	199	**31**	39	1467
7	21	220	**32**	76	1543
8	22	242	**33**	97	1640
9	25	267	**34**	19	1659
10	38	305	**35**	37	1696
11	27	332	**36**	15	1711
12	14	346	**37**	17	1728
13	23	369	**38**	91	1819
14	36	405	**39**	47	1866
15	20	425	**40**	8	1874
16	23	448	**41**	28	1902
17	16	464	**42**	50	1952
18	123	587	**43**	28	1980
19	25	612	**44**	63	2043
20	23	635	**45**	110	2153
21	59	694	**46**	93	2246
22	7	701	**47**	12	2258
23	43	744	**48**	77	2335
24	36	780	**49**	27	2362
25	15	795	**50**	123	2485