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The Prediction Trend of Production in Decision Support System Based on ARIMA-Artificial Intelligence

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Abstract: The Industrial Era 4.0 has seen industries start shifting towards implementing Decision Support System (DSS) in the manufacturing sector. Technological advancements have made it possible for the development of DSS to be based on Artificial Intelligence (AI) using past data generated by industry, especially in the furniture manufacturing industry. The furniture manufacturing industry is now faced with the challenge of Extreme Programming (XP) model complexity that hinders production and inventory management. The manufacturing industry finds it difficult to comprehend which industries to produce based on the current market trends. This research, therefore, seeks to comprehend how an AI-based DSS system can learn furniture model production trends. Based on such problems, this research can potentially assist in designing an AI-based DSS employing the Autoregressive Integrated Moving Average (ARIMA) model from the XP system development paradigm. This research is segmented into five phases, i.e., problem identification, decision model design, data collection and processing, system development and integration, and implementation. The delivery of this research is a list of best-selling furniture fads from market analysis generated through DSS. These findings are useful in the development of DSS, especially in AI to make predictions of furniture model trends.

Keywords: Artificial intelligence; Decision support system; Autoregressive Integrated Moving Average model; Extreme programming; Furniture

JEL Classification: L63, O33, D24

1. Introduction

The era of the industrial revolution 4.0 has welcomed the manufacturing industry to shift towards the application of information technology (Abiodun et al., 2022; Javaid et al., 2022). The furniture manufacturing sector is now shifting towards applying the Decision Support System (DSS) to help analyze previous data based on the business processes carried out (Andry et al., 2022a). The DSS architecture is divided into three large layers, i.e., the interface, processing, and data collection which are tied together to form an application that pulls out information at any moment (Bazilevych et al., 2022; Romanenko et al., 2021; Ryu et al., 2023). Previous research conducted by Mahdi et al., stated that the deployment of DSS should be supported by Artificial Intelligence (AI) technology as a way of aiding in the analysis of future projections (Mahdi et al., 2021). The implementation of AI makes use of learning from previously available data (Romaniuk & Łukasiewicz-Wieleba, 2024). AI is vastly being utilized for coming up with smarter technology of the future for several applications (Sharmila & Florinabel, 2022). Past studies by Sharma et al. (2024), presuming AI is a computer or machine ability to learn and build performance on the same activity with a larger slope over a passage of time. Therefore, AI applications are incorporated into DSS for real-time decision-making and predicting future trends (Rojek & Dostatni, 2020; Zhang & Goyal, 2024). Theoretical underpinning of AI in DSS utilizes the Autoregressive Integrated Moving Average (ARIMA) model to obtain the latest business process trends.

The development of AI-based DSS utilizes the use of ARIMA models to predict and analyze prevailing trends in the industry (Kontopoulou et al., 2023; Lu et al., 2022). ARIMA is a statistical model utilized for time series data analysis and prediction (Dimri et al., 2020; Khan & Alghulaiakh, 2020). Dong et al. (2024), in their prior work, noted that the ARIMA regression model is utilized to predict development trends in the industry. The process of implementing ARIMA begins with data collection, data cleaning, and processing data with the Python programming language (Lai & Dzombak, 2020; Nkongolo, 2024). The manufacturing industry currently faces the problem of the complexity of furniture models that hampers production and stock levels. The manufacturing industry cannot determine which furniture models should be produced based on current market trends. Without forecasting, the furniture industry can be hit by overproduction or understocking. By predicting the most popular models, the industry can prioritize production processes. Although various previous studies have examined the application of ARIMA for forecasting in an industrial context, most of these studies still focus on isolated data analysis and have not been directly integrated into the DSS used in daily industrial operations. Furthermore, previous ARIMA studies generally use conventional data processed offline, so the forecasting results do not fully support real-time decision-making that is adaptive to market dynamics. Furthermore, DSS developed in previous studies often serve only as reporting and visualization tools for historical data, without directly embedding AI models as the core of decision-making. This condition makes DSS less than optimal in providing products that will become trends.

Based on these research gaps, the novelty of this study lies in the direct integration of the ARIMA model as a core AI component in a DSS developed using the Extreme Programming (XP) methodology. Unlike previous studies that used ARIMA as a separate analysis tool, this study embeds ARIMA into the DSS so that the forecasting process, trend analysis, and decision recommendations can be carried out in an integrated and sustainable manner. Furthermore, this study emphasizes the use of direct industrial operational data to predict trends furniture models in the market. The forecasting results are used not only as statistical information but also as a basis for product grouping. This approach allows the industry to focus production resources on furniture models with the highest potential, thereby increasing production efficiency and reducing the risk of overproduction and understocking. Although the combination of DSS and ARIMA has been widely explored in previous research, this study does not focus on developing a complex AI model, but rather on implementing a forecasting model that is interpretive, stable, and easily integrated into industrial decision-making processes. The omission of a direct comparison with modern AI/ML models such as LSTM is a recognized limitation, given that the primary objective of this study is to build a practical, computationally lightweight DSS that can be adopted by medium-sized manufacturing industries that generally have limited data and computing resources. This study therefore positions its contribution in the area of data-driven decision support through system integration, decision support functionality, and agile XP-based system development, rather than in the advancement of sophisticated AI models.

2. Related Works

DSS with AI

AI-based DSS development facilitates businesses to use advanced tools to make choices quickly (Deveci et al., 2024; Gupta et al., 2021). On the other hand, AI-based DSS leverages AI to predict future trends. DSS that uses AI algorithms to enhance knowledge and optimize the management of company processes. The use of AI in DSS is a significant momentum for applications in various fields (Chen et al., 2024; Higgins et al., 2023).

ARIMA

Forecasting is one of the statistical methods that plays an important role in decision making (Chodakowska et al., 2021; Hanifi et al., 2020). One of the methods used in forecasting is the time series method based on past information from a variable or past errors. The forecasting method commonly used is the ARIMA which uses past and present values of the dependent variable to produce short-term forecasts (Sirisha et al., 2022).

XP

The widespread use of AI in recent years has caused rapid progress in its adoption with technology (Ignatius et al., 2022). Intelligent devices and software will continue to dominate the technology market (Yang et al., 2024). XP system development framework is a step-by-step system development approach for designing a user-centric and data-driven DSS. Steps of XP methodology are categorized into five steps that include needs planning, decision model design, building the system, testing, and implementation. According to research carried out by Saxena, DSS organization with XP involves detection of technology implementation and user need (Saxena, 1991).

3. Method

The research flow carried out in this study is shown in Figure 1.

1. Planning requirements. This stage aims to identify the key issues faced by the furniture manufacturing industry as the research object, particularly in predicting model trends. The organizational context of the research

is a medium-sized furniture manufacturing company producing various furniture models for the domestic market, with an operational system that routinely records production data. The data source used is the company's internal operational system (production transaction database), which is used directly in daily business activities. Characteristics of the data used in the research: historical production data for the furniture manufacturing industry over a five-year period (2020–2024) with a monthly data frequency. The dataset consists of 10 major furniture models, with approximately 60 observations for each model, resulting in a total of approximately 600 observations used in this study. The selection of a five-year timeframe and a monthly frequency aim to capture medium-term trend patterns and seasonal variations.

2. System Design. This stage is meant to define the requirements that need to be met in terms of users, decision models, and hardware/software.

3. System Development and Integration. The development of the ARIMA model is carried out separately before being integrated into the DSS, with the following stages: Data preprocessing (data cleaning), determining ARIMA parameters (p, d, q) through data stability analysis and historical data relationship patterns, then selecting the model with the most efficient prediction performance, training the ARIMA model using historical data according to a predetermined period, initial testing of the model to ensure the model is able to capture data trend and seasonal patterns. At this stage, the performance of the ARIMA model is evaluated using quantitative evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Experimental validation is conducted using industrial operational data to compare the system's prediction results with actual data, so that the research is not merely conceptual, but supported by real-world testing results.

4. System Implementation. The DSS, designed in the previous stages, is implemented here. The prototype carries the basic features of the system, including the implementation of an ARIMA model, a basic user interface, and limited functionality in analyzing and displaying predictions.

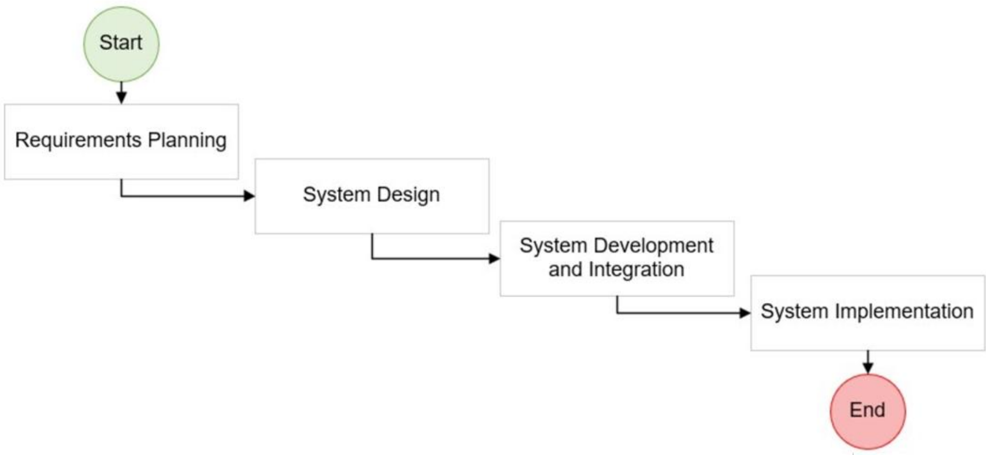

Figure 1. Research stages (Mora et al., 2010)

4 Results

4.1 Planning Requirement

This subsection identifies business processes that exist in the manufacturing industry and defines major issues addressed by DSS (Andry et al., 2023). It is only after ascertaining the status of the business process of the manufacturing industry that trend analysis is possible based on AI tools.

The industry business process of the current era starts with a customer order a furniture model with definite specifications for the marketing department, and the latter creates an order letter to complete the order. The production department is given the order letter by the marketing department. The production department issued a Work Order (WO) to begin the process of manufacturing furniture and check the availability of raw material stocks. If the raw material is not in stock, then the production department orders raw material from the supplier. After the supplier dispatches the raw material, the production department goes directly into the process of production. The following business process is the process of orders for custom products from customers until the product delivery is complete. The turning points are when verifying the raw material stock, which determines if the production process can be started immediately or must wait for the raw materials to arrive from the supplier. To solve the problems of the current industry business process, here is a mapping of AI implementation solutions for DSS in Table 1.

Table 1. Solution mapping (Russ-Jara et al., 2021)

Element	Description
Problem Identification	Too many variations of furniture models.
Artificial Intelligence (AI) Decision Support System (DSS) Objectives	Predicting furniture models that will become trends.
Supported Decisions	Best selling models.
Decision-Making Tasks	Determine AI predictions for model trends.
Required Data	Production data of all model in industry.
Constraints or Limitations	Reliance on the accuracy of AI predictions to follow trends.
Output	Recommendations for model trend.
User Benefits	More accurate and minimize waiting time.

4.2 System Design

Design creation provides an overview of the DSS that must be provided to support decision-making (Carneiro et al., 2021). This section outlines the design requirements of the DSS against three phases:

1. User Analysis. This is where end user requirements in the use of the DSS (Raparthi et al., 2021) are examined and categorized by expected output. Production Manager (report on furniture trend forecast), Production Admin. (ranking of the priorities according to furniture models trends), Marketing Manager (trend forecast report on the best-selling furniture models), Marketing Admin (top-selling furniture models)

2. Decision Model Analysis. Analysis focuses on the decision model used in selecting furniture production strategies (Cinelli et al., 2020; Mustak et al., 2021). The data utilized for examples in this instance is presented in Table 2.

Table 2. Example of raw data for AI modelling

Date	Model	Qty	Unit Price
04/01/2020	Parma II	79	1.460.000
04/01/2020	Parma I	25	1.920.000
04/01/2020	Aristocrat II	1	1.705.000
05/01/2020	Parma II	176	1.701.700
05/01/2020	Chelsea III	168	1.601.600
09/01/2021	Napoli II	60	2.343.000
09/01/2021	Napoli II	14	1.874.400
09/01/2021	Napoli IV	16	1.551.000
09/01/2021	Senator I	8	2.651.000
09/01/2021	Napoli III	14	1.340.000

Table 2 provides a representation of furniture model report utilized in the creation of the AI model to predict the most popular models. The date column represents the period when production occurred, which is crucial for monitoring trends over time. The model column displays the name of furniture that is sold and serves as the most important subject to trend analysis. The qty column shows the amount of furniture units sold on this date. The unit price column shows the price per unit for the furniture model.

3. Hardware/Software Environment. Software for developing DSS and hardware supporting its functioning are identified (Andry et al., 2022b; Wang et al., 2021). Hardware environment, it requires a local/cloud server to deploy the DSS system, computers, Graphics Processing Units (GPUs) and networks. Software environment includes operating systems, database management systems, data processing tools, machine learning/AI frameworks.

4.3 Development

This phase gives specifications for AI modeling in DSS prior to proceeding with the implementation phase that consists of three phases.

1. AI Development for Forecasting Single Model. At this stage, a decision model is created that constitutes the foundation of the recommendations provided by the DSS (Ponomarev & Mustafin, 2021). AI model development utilizes the ARIMA method and Python programming language. Before looking for the trend of best-selling furniture, forecasting is done on certain models of furniture. By implementing it on one furniture model, we can verify the ARIMA model's validity in predicting the production on a small scale first, before we implement it with multiple models using the step. The first step, specify the model of furniture. In this case, one of the furniture models, "Sofa Living", is chosen from the monthly production data. Divide the data to train the model and test as

reference data for validating the prediction results. Train the ARIMA model. Make production predictions for the next 12 months. Visualize the prediction results in Figure 2.

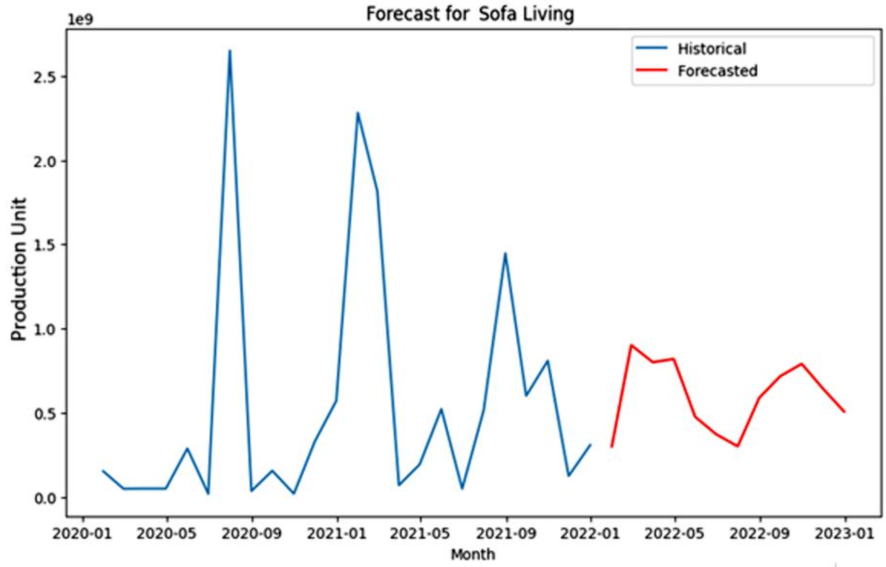

Figure 2. Prediction results for production trend of one model

Figure 2 shows how the ARIMA process is applied to predict production trends within one model. The horizontal axis (month) is the production time range, with previous production data. The vertical axis (production) is the potential production quantity of the product. The blue line shows previous production data for the model. This data is used by ARIMA model to study the seasonal pattern, trend, and fluctuation of production of this product. Red is the line of production prediction with the trend of fluctuation having an upward and downward slope following the same trend of history. The pattern predicted by the ARIMA model provides an idea of the possible increase or decrease of the model in the coming year. One furniture model being considered as in Figure 2 makes it easier to understand the pattern. When all models are considered collectively at a time, this individual pattern gets lost in the overall data and thus the prediction becomes less precise.

2. AI Development for Prediction All Model. Subsequently, the ARIMA method is used to determine the general trend of furniture models by the following step:

• Data Grouping per Model. In this research, data used has a time range of January 2020–December 2024, with the amount of data per model being 60. So, the total research data is 600. Each model is treated as an independent time series to capture its unique production pattern.

• Training and Testing Data Distribution. The training data from 2020–2023 consisted of 480 data sets and the testing data set consisted of 120. This separation was intended to evaluate the model's ability to predict actual data that had not been used in training. The testing phase simulates real industrial conditions where future production must be predicted without access to actual values.

• Model Determination and Training. An ARIMA model was developed to capture monthly production patterns based on historical data relationships and error correction mechanisms. Prior to model training, stationarity testing was performed using the Augmented Dickey-Fuller (ADF) test to ensure the suitability of the data for time series modeling. The test results indicated that the original data were non-stationary, and first-order differentiation was required to achieve stationarity. Therefore, the differentiation order was set to $d = 1$, resulting in the use of an ARIMA (1,1,1) model. The selection of the autoregressive term (p) and moving average (q) has been explained by describing the analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots in the Model Determination and Training subsection. The PACF shows a significant break at lag 1 ($p = 1$), while the ACF shows a significant spike at lag 1 ($q = 1$). Several candidate ARIMA models, including ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (2,1,1), were evaluated to determine the most appropriate configuration. Model selection was based on a comparison of Akaike Information Criterion (AIC) values and forecasting performance. The ARIMA (1,1,1) model was selected as it consistently produced the lowest AIC value and stable residual patterns, indicating an optimal balance between model accuracy and model simplicity. Parameters were estimated using training data from 2020–2024, and the trained model was then used for forecasting.

• Forecasting and Visualization. The trained ARIMA model was used to predict 12-month production for each furniture model. The predicted results are directly compared with actual production data in Table 3.

Table 3 shows that the ARIMA predictions closely follow the actual pattern with a small difference (±1–2 units), used to evaluate the accuracy of the ARIMA forecasting model by comparing predicted and actual values.

Table 3. Forecast result vs. actual data

Month (2024)	Actual (Unit)	Autoregressive Integrated Moving Average (ARIMA) Forecast (Unit)	Gap
January	92	90	2
February	95	93	2
March	97	95	2
April	96	98	-2
May	99	100	-1
June	101	103	-2
July	104	106	-2
August	103	104	-1
September	105	107	-2
October	106	108	-2
November	108	110	-2
December	110	112	-2

Table 4. Forecast result vs. actual data

Rank	Model Identifier	Cumulative Forecast (Unit/Year)
1	Senator III	1,248
2	Sofa Living	1,185
3	Senator II	1,132
4	Senator I	1,098
5	Napoli IV	1,054
6	Napoli I	1,012
7	Sevilla II	978
8	Napoli II	945
9	Aristocrat V	917
10	Phinisi	889

Table 4 presents the ranking of furniture models based on cumulative forecasts over 12 months, which serves as the quantitative basis for selecting the Top 10. The visualization results are shown in Figure 3.

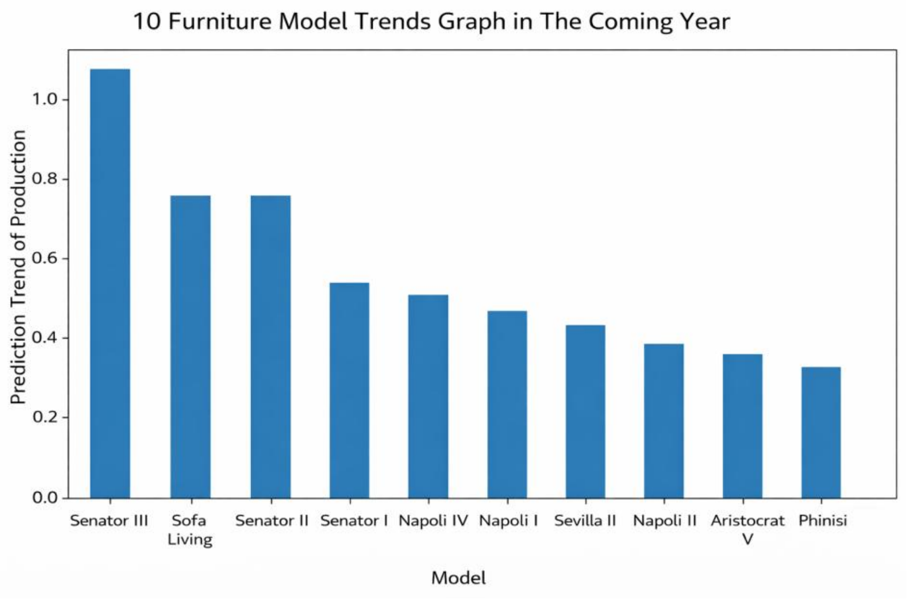

Figure 3. Bar chart of ten furniture model trends in next year

Figure 3 depicts the results of the ten furniture model trends graph in the coming year. This trend is based on the result of the AI analysis incorporated in the DSS. The use of historical helps predicts. The Top 10 models were selected based on the cumulative predictive value over the next 12 months. The models with the highest cumulative predicted values were then ranked and selected as the ten models with the greatest production potential.

• Evaluation of Accuracy. Prediction accuracy evaluation. Model performance is evaluated using three standard metrics: MAE, RMSE, and MAPE in Table 5.

Table 5. Autoregressive Integrated Moving Average (ARIMA) evaluation results

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Mean Absolute Percentage Error (MAPE) (%)
Senator III	3,94	4,81	3,69
Sofa Living	5,05	5,89	7,44
Senator II	3,85	5,40	3,96
Senator I	3,94	4,87	4,26
Napoli IV	3,68	4,57	4,71
Napoli I	2,66	4,03	2,81
Sevilla II	3,66	4,79	3,89
Napoli II	5,27	6,72	6,06
Aristocrat V	5,07	5,98	5,61
Phinisi	4,44	4,77	4,37

Table 4 shows that the majority of MAPE models are between 2–7%, which proves the claim of increased prediction accuracy if it is below 10%. In addition to the accuracy evaluation, residual diagnostics were performed to assess the adequacy of the ARIMA model. Visual inspection of the residual time series plots showed that the residuals fluctuated randomly around zero without exhibiting any systematic pattern. Furthermore, residual autocorrelation analysis showed that most autocorrelation values were within the confidence limits, indicating the absence of significant serial correlation. To statistically confirm this observation, the Ljung–Box test was applied, and the results showed a p-value greater than 0.05, indicating that the residuals behaved as white noise. This finding confirms that the selected ARIMA model is appropriate and does not leave significant information unexplained.

4.4 Implementation

The final step of developing a DSS with AI is to develop a prototype of the DSS with an AI model, a basic user interface, and a core workflow (Bohm & Graser, 2023), as in Figure 4.

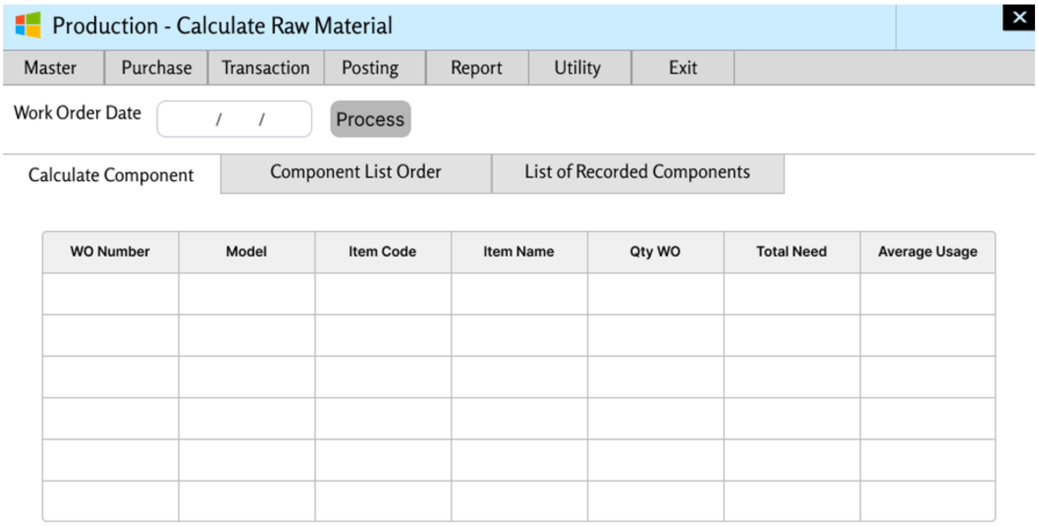

Figure 4. Example of implementation Decision Support System (DSS)

Figure 4 represents the use of DSS in the manufacturing department so that the usage of raw material can be calculated that records details such as WO number, model, code, name, and various other different details of stock allocation. Products are produced with consideration of that model, which is selling the most, so that the calculation of raw material might be carried out more accurately. With the understanding of how much production is needed, DSS will be able to calculate how much raw material will have to be provided. Predictive data allows for better planning for acquiring raw material, such that production is not put on hold.

The result of AI conceptualization on DSS using the ARIMA method in the form of furniture model trends that were most purchased last year to be utilized in mass production and the formula for calculating raw materials. The depiction of the DSS approach that has been infused with AI for predicting furniture model trends is shown in Figure 5.

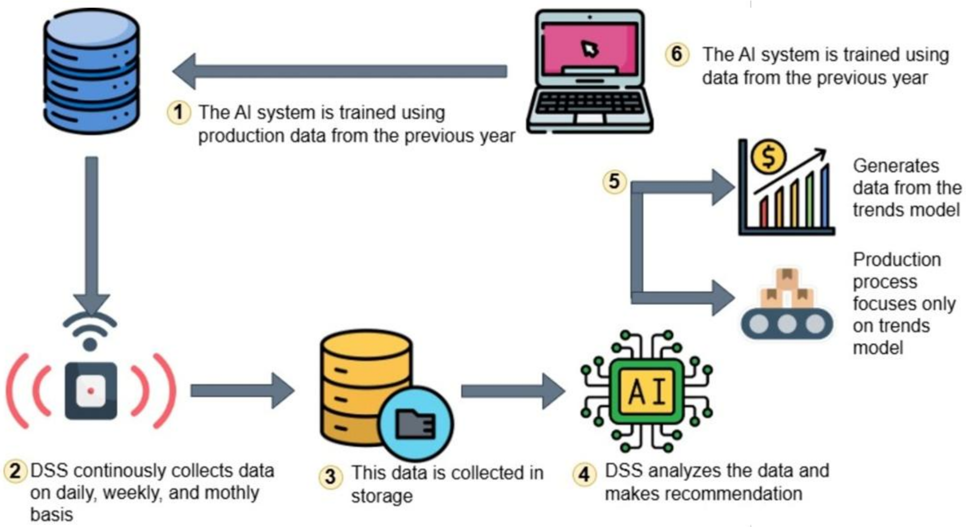

Figure 5. Artificial Intelligence (AI) process in Decision Support System (DSS)

Figure 5 shows how AI is conceptualized in DSS. The processing stages in DSS are as follows:

1. The AI system uses data from the past. AI can analyze past production data of furniture products to forecast trends. This helps the industry avoid stock shortages. This historical data is the basis for training the ARIMA model, so the system can predict future trends.

2. The sensors from the DSS collect data on various operational parameters that affect furniture model trends. These parameters are models and unit production. The DSS continues to collect production data on a daily, weekly, and monthly basis. This allows the DSS to have up-to-date data to make accurate analyses.

3. This data is collected/uploaded to DSS data storage. The collected data is stored in the data storage, becoming a reference center for the DSS to perform analysis and trend calculations.

4. The DSS analyzes the data and makes recommendations. Using the ARIMA model, the DSS generates production trend predictions, which are then used to make recommendations.

5. There are two suggestions generated by the DSS. The first recommendation is related to furniture model trends in the industry. The production department focuses on models that are predicted to sell well, so that production can be directed at the right models.

6. Actual data from failures is fed back into the AI system to improve its accuracy in the future. This is known as learning from failure data or reusing failed data. A concrete example experienced by the furniture industry is that there is production data for furniture models. This data is used as a reference to improve furniture models that are still not selling well. When furniture experiences poor production, data regarding this failure is recorded in detail, including information on product defects.

This stage conducted through functional testing to ensure that each system module operates according to defined requirements, including the integration of the ARIMA model into the DSS and the presentation of prediction results. Formal user testing, such as measuring usability or user satisfaction, has not yet been conducted and is planned for future research.

5. Conclusions

This study demonstrates the successful development and implementation of DSS that integrates the ARIMA forecasting model using the XP methodology to support production decision-making in the furniture manufacturing industry. By utilizing five years of historical operational data, the proposed system is able to forecast monthly production, identify trends, and objectively rank furniture models based on cumulative forecasted trends. The results show that the ARIMA-based DSS can produce reliable forecasts with acceptable accuracy. Rather than proposing a complex AI model, this research emphasizes an interpretable and computationally efficient forecasting approach that can be easily adopted by medium-scale manufacturing industries with limited data and computing resources. Nevertheless, this study has several limitations. The forecasting model relies solely on internal historical data and employs a univariate ARIMA approach, which does not account for external factors or complex inter-variable relationships. Future research is therefore recommended to incorporate exogenous variables and to explore hybrid forecasting models, such as ARIMA-LSTM, as well as to conduct more comprehensive user evaluations to further enhance the adaptability and effectiveness of the DSS in dynamic market environments.

Author Contributions

Conceptualization, J.F.A. and K.C.; methodology, A.C., F.S.L., and L.L.; software, F.S.L.; validation, J.F.A., A.C., K.C., F.S.L., and L.L.; formal analysis, A.C., F.S.L., and L.L.; investigation, J.F.A., K.C., and L.L.; resources, J.F.A.; data curation, K.C. and L.L.; writing—original draft preparation, J.F.A. and L.L.; writing—review and editing, J.F.A. and L.L. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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