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BALANCING MATERIAL SUPPLY-DEMAND WITH ARIMA AND NEURAL NETWORKS

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Abstract
This study introduces a hybrid Autoregressive Integrated Moving Average Model-Back Propagation (ARIMA-BP) neural network model to improve the accuracy of production material demand forecasting amid growing market competition and diverse customer requirements. By integrating both linear and nonlinear elements, the model enhances efficiency in production planning, inventory optimization, and operational cost reduction. It explores novel methods to align supply and demand, optimizing the interplay of material procurement, product output, and inventory management. The study's key contribution is a forecasting approach that informs balanced production strategies, with significant implications for operational effectiveness and competitive advantage in manufacturing.
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Key Words: Production Material Demand Forecasting, Supply Balance Strategies, ARIMA-BP

1. INTRODUCTION

In modern production management, strategies for material demand and supply balance have been recognised as essential elements to augment the operational efficiency of manufacturing enterprises, reduce associated costs, and fortify market competitiveness [1-3]. It has been observed that precise forecasting of production material demands serves as a cornerstone for robust decision-making, thereby enabling refined planning of production endeavours, inventory level optimisation, and risk mitigation associated with inventory stock-outs or surpluses [4]. However, traditional forecasting methodologies are reported to be inadequate in navigating the intricacies of swiftly evolving markets and intricate production operations. As a result, the quest for a precise time-series forecasting model, pivotal for establishing a production plan congruent with supply and demand equilibria, has garnered substantial attention, citing its implications for optimal orchestration of material and financial channels [5-9].

Several lacunae and limitations within extant research paradigms pertaining to production material demand forecasting have been delineated [10, 11]. Notably, individual time-series forecasting models often encounter challenges in concurrently deciphering linear and nonlinear data associations, culminating in compromised forecasting accuracy [12]. For instance, while the ARIMA's capacity to decipher nonlinear patterns has been acknowledged as limited, isolated neural network models are reported to require vast datasets to avert overfitting and entail meticulous data preprocessing [13, 14]. Additionally, a significant portion of prevailing research seems to fall short in cohesively melding demand forecasting with supply balance strategies, resulting in production designs that manifest reduced adaptability and versatility. Furthermore, the ramifications of erratic market shifts and unprecedented events on material demand forecasting, often neglected, potentially undermine the practical reliability and robustness of such models [15, 16].

This investigation primarily bifurcates its focus into two domains. The preliminary domain addresses production material demand forecasting anchored in a time-series model. Within this

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ambit, an ARIMA-BP neural network amalgamated model has been delineated, seamlessly integrating the prowess of the ARIMA in elucidating linear attributes of time-series data with the BP neural network's aptitude for nonlinear fittings. Through the adoption of this hybrid model, enhancements in forecasting accuracy and the model's resilience against multifaceted data have been observed. The ensuing domain concentrates on devising production strategies underscored by supply-demand congruence. Deliberations centred on optimally balancing material procurement expenditures, calibrating product outputs, and bolstering product inventory have paved the way for an avant-garde production planning methodology. This approach, as evidenced, underpins a seamless production trajectory, catering to market demand ambivalence, curtailing resource squandering, and amplifying the market acuity and adaptiveness of manufacturing entities. The essence of this research is encapsulated in its novel vantage point on production material demand forecasting complexities and its pioneering synthesis with supply-demand equilibria, thereby delineating a comprehensive production planning framework. The findings herein are poised to resonate profoundly, steering tangible production management efforts, refining resource distribution, and enhancing the competitive leverage of manufacturing entities.

2. PRODUCTION MATERIAL DEMAND FORECASTING BASED ON A TIME SERIES FORECASTING MODEL

For manufacturing enterprises, accurate and robust production material demand forecasts are of paramount significance. Such forecasts are believed to furnish these enterprises with the tools needed for devising effective production blueprints, executing meticulous inventory controls, and making judicious production material procurement decisions amidst uncertain market terrains. Direct implications are drawn between these forecasts and strategies aimed at cost diminution and optimal resource distribution, but it is also postulated that they provide potent data scaffolding at the operational echelon. This scaffold, in turn, is seen as an enabler for manufacturing enterprises, assisting them in nimbly navigating market perturbations, amplifying market competitiveness, and preserving a trajectory of sustainable growth in the face of rigorous market rivalry.

Against this backdrop, an innovative time series forecasting model that synergises the ARIMA with the BP neural network has been proffered, targeting the enhancement of precision in forecasting production material demand. This hybrid model is discerned to judiciously harness the ARIMA's facility in addressing linear nuances of time series data in conjunction with the BP neural network's acumen in mirroring nonlinear intricate relationships. Such a blend is seen to effectively bridge the gaps encountered by traditional monolithic models when confronted with the dual challenges of linear and nonlinear data features.

Within the practical realm of production material demand forecasting, it is observed that demand data typically amalgamates predictable linear trajectories with sporadic nonlinear configurations. The linear facet primarily encapsulates stable evolutionary patterns, seasonal oscillations, and variations tied to production cycles, historical sales metrics, inventory calibrations, and material turnover rates. All these dimensions, it is argued, are adeptly mirrored and anticipated by the ARIMA. However, a singular linear analysis is perceived to be bereft of capturing all data complexities, especially in the throes of market dynamism and unpredictable consumer predilections. It is these nonlinear attributes, manifesting as stochastic oscillations and unanticipated event imprints, that conventional linear paradigms grapple with. However, the BP neural network, renowned for its prowess in nonlinear schema discernment, is seen to effectively learn and reflect these intricate paradigms. Thus, by juxtaposing the linear predictive capabilities of the ARIMA against the nonlinear fitment strengths of the BP neural network, it is believed that not only are the intricacies of time series data more holistically embraced, but the overarching forecasting accuracy and sturdiness are also amplified via the reciprocity of both frameworks.

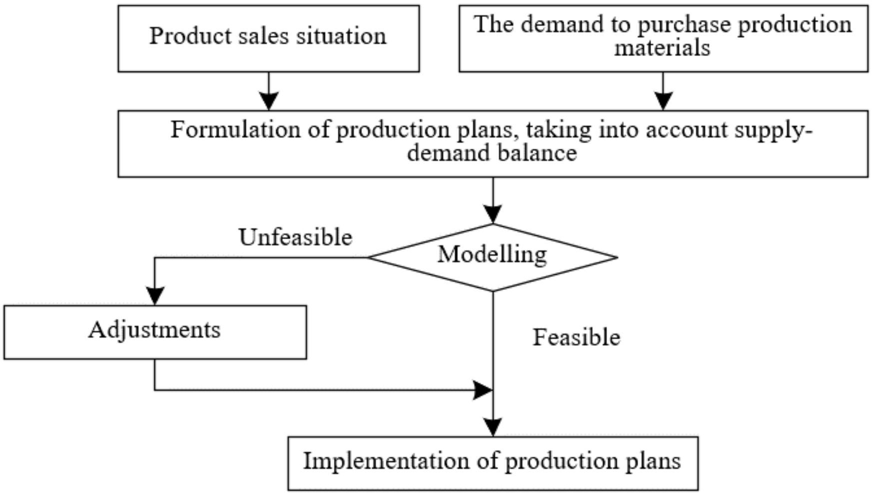

Figure 1: Production material demand forecasting pathway based on ARIMA-BP neural network.

Fig. 1 offers a visualisation of the ARIMA-BP neural network-based forecasting pathway for production material demands. The process of forecasting production material demands through the use of the ARIMA-BP neural network has been compartmentalised into three distinct steps:

Step 1: Employment of the ARIMA. The ARIMA is utilised to forecast F_y, with the forecasted outcome denoted as $\hat{X}_y$. The deviation between the original series and the predicted results from the ARIMA is delineated as r_1. This residual can be mathematically represented as:

$$r_y = F_y - \hat{X}_y \tag{1}$$

In this scenario, random errors are depicted by γ_y and the non-linear function by d. The inherent non-linear relationship in the original series, found within the sequence $\{r_y\}$, can be captured by:

$$r_y = d(r_{y-1}, r_{y-2}, \cdots, r_{y-b}) + \gamma_y \tag{2}$$

Step 2: Integration of the BP neural network. The BP neural network, built upon the foundational principles of the genetic algorithm, is employed to predict the sequence $\{r_y\}$, resulting in the forecasted outcome $\hat{r}_y$.

Step 3: Fusion of ARIMA and BP neural network forecasts. In this final step, the linear forecast outcomes from the ARIMA are amalgamated with the BP neural network's predictions for the non-linear portion of the residual series. Such a synthesis takes into consideration both the primary linear structure of the data and its nuanced non-linear tendencies, ultimately providing a holistic forecast for production material demands. If the demand at a specific time y is denoted by X_y, the optimal forecast result of the ARIMA by $\hat{X}_y$, and the BP neural network's predictions by $\hat{r}_y$, the comprehensive forecast result can be described as:

$$\hat{F}_y = \hat{X}_y + \hat{r}_y \tag{3}$$

Within the BP neural network's structure, it is acknowledged that the number of neurons in the input layer and the hidden layer are signified by l and b respectively. The interrelationship weights between the neurons in the input layer and those in the hidden layer are defined by β_k (where $k = 0, 1, ..., b$), while the weights governing the relationship between neurons in the hidden layer and the output layer are expressed by α_{uk} (where $u = 0, 1, l$; $k = 1, 2, ..., b$). Keeping the structural characteristics of the BP neural network in mind, the model can be adjusted to:

$$r_y = \beta_0 + \sum_{k=1}^{b} \beta_k d\left(\sum_{u=1}^{l} \alpha_{uk} r_{y-i} + \alpha_{0k}\right) + \gamma_y \tag{4}$$

3. FORMULATING PRODUCTION PLANS CONSIDERING SUPPLY-DEMAND BALANCE

In contemporary industrial operations, discrepancies between material supply and demand have been observed to elevate operational costs and diminish process efficiency. The paramount importance of precise demand forecasting in fostering logical production plan design is recognised. Such design is essential to efficiently reduce inventory costs, avert the risk of stock-outs, and elevate resource utilisation efficiency. With the integration of a refined time-series forecasting model, research has been undertaken to design production plans that carefully consider supply and demand balance. Particularly in scenarios where market demand experiences substantial dynamic shifts and uncertainty, this investigation lays the groundwork for bolstering the adaptability and promptness of production planning. Consequently, this contributes to augmenting the financial viability and market competitiveness of manufacturing entities.

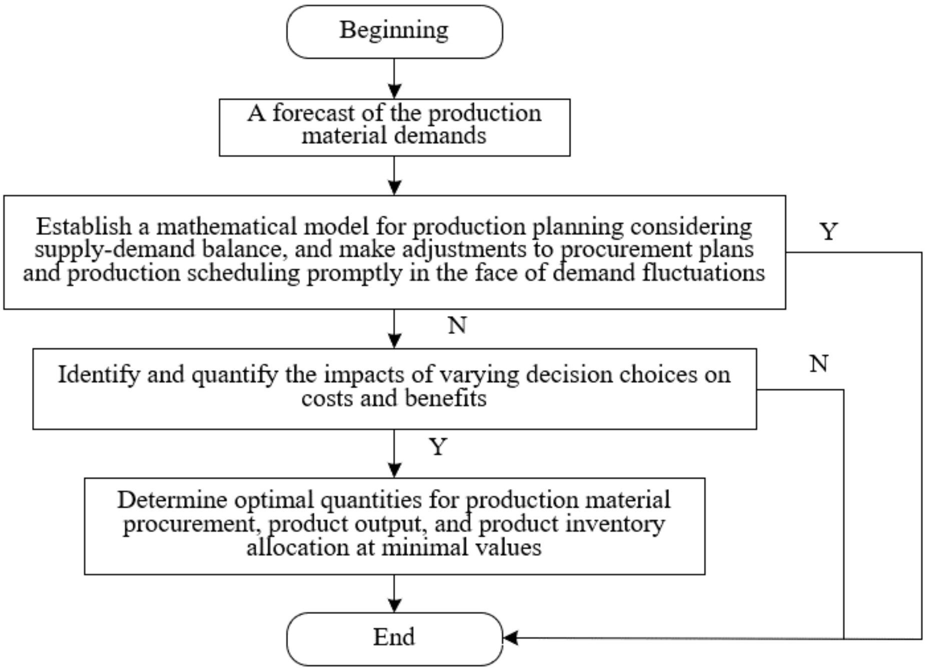

Figure 2: Ideas of production plan formulation considering supply-demand balance.

Fig. 2 delineates the conceptual foundation of formulating production plans that are balanced with respect to supply and demand. The underpinning aim of the mathematical model was to minimise the cumulative cost encompassing "production materials-product output-product inventory". This model synergistically merges production planning with inventory optimisation tactics. Fig. 3 offers a synopsis of the model's input-output dynamics. Regarding production material inventory costs, both holding expenditures (spanning storage overheads, insurance premiums, and financial levies on materials) and risk-associated costs (relating to potential losses stemming from material surpluses or deficiencies) were integrated. Such losses might manifest as material obsolescence, damage, or missed revenue opportunities due to disrupted supply chains. Analogously, for product inventory costs, both holding costs, incurred due to locked inventory capital and storage levies, and risk-associated costs, attributed to potential devaluation or promotional outlays when facing product surplus or deficits, were incorporated. Production output costs primarily concentrated on infrastructural costs of the production facility and remuneration for the workforce. The expenses tied to production infrastructure covered aspects like machinery depreciation, routine maintenance, and energy overheads. These span both fixed and variable components. Meanwhile, workforce compensation was gauged in tandem with variations in production output.

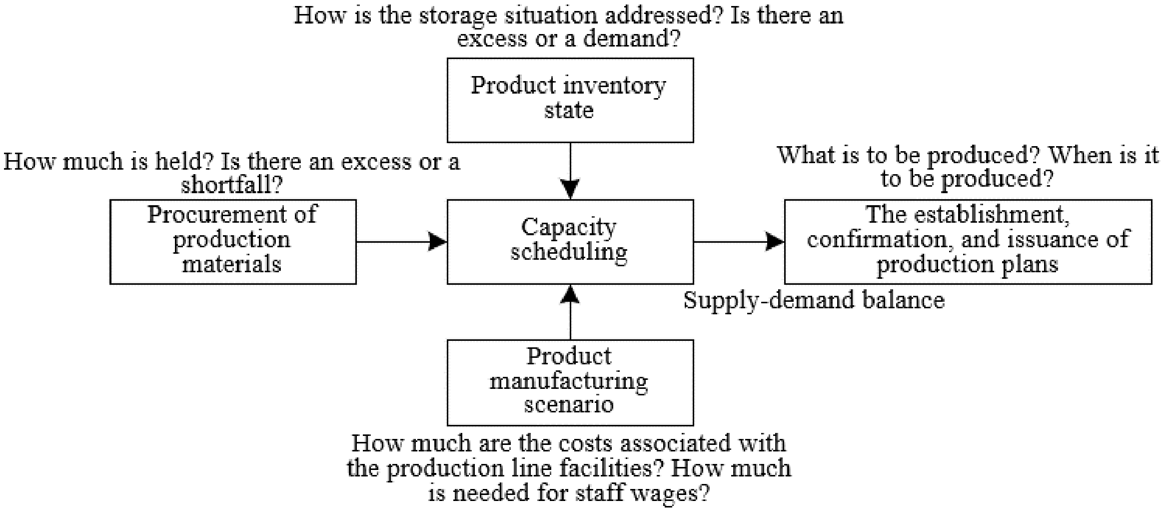

Figure 3: Input-output relationships of the mathematical model.

In the pursuit of refining industrial production planning, a mathematical model is constructed, wherein the alignment between the quantity (W) of production materials and the volume (V) of producible goods within a manufacturing entity is assessed monthly. The unit cost associated with producing each product is denoted as CBY_{LI}. Monthly market demands, forecasted across a year, are represented by a series of predictions Pef_1, Pef_2, Pef_3, ..., Pef_{12}, with corresponding production material requirements expressed as Prf_1, Prf_2, Prf_3, ..., Prf_{12}. Periods of demand peaks and troughs are symbolised by H_u and f_u, respectively, for any given month ($1 \leq u, k \leq 12$).

A surplus in the product output relative to the forecasted market demand within a specific month is represented by a positive value of F_l. For the l^{th} month, the disparity between the volume of production and the anticipated market demand is quantified through the subsequent equation:

$$F_l = V - Pef_l, l = 1, 2, 3, \ldots, 12 \tag{5}$$

A positive value of F_l indicates a surplus in product output, while a negative value denotes a deficit. Balance is indicated by F_l equalling zero, reflecting a balance between supply and demand. Over a 12-month period, the deviation between actual material usage for production and the forecasted requirements is cumulatively presented as $\Sigma^{12}{}_{l=1}C_l = C_1 + C_2 + \ldots + C_{12} = (W\text{–}Prf_1) + (V\text{–}Prf_2) + \ldots + (V\text{–}Prf_{12})$. A zero sum suggests a precise congruence between anticipated material needs and actual consumption, epitomising the forecast model's accuracy and thus the minimisation of inventory and risk costs. The investigation focusses on refining the forecast model to reduce the likelihood of production disruptions or shortages, whilst evaluating the consequences of demand underestimation on production and inventory management. This entails developing robust production strategies and contingency protocols, primarily addressing scenarios with a positive aggregation sum.

Further, a range is delineated for the average additional monthly product output, denoted as $[0, min(F_1, F_2, ..., F_{12}) \times (-1)]$, and for the monthly increase in procurement of production materials, set as $[0, min(C_1, C_2, ..., C_{12}) \times (-1)]$. The incremental monthly product output is represented by V_r, with the annual cost of this additional output expressed as $CBYC_e$. The number of additional production lines required for the increased output is calculated as V_r/V_{fz}. Here, V_{fz} denotes the average monthly output per production line, V_{zt} the existing monthly product output, and V the target monthly product output. The operating cost per production line is denoted by CBY_{LI}, leading to the formulation of the following Eq. (6).

$$CBY_{V_r} = \left(V_r/V_{fz}\right) \times CBY_{LI} \times 12 = \left[(V - V_{zt})/V_{fz}\right] \times CBY_{LI} \times 12 \tag{6}$$

Eq. (6) enables the computation of the additional procurement of production materials.

Both the inventory costs of production materials and finished products encompass holding costs and risk costs. This study delineates the detailed cost factors within these categories. The monthly inventory cost for a unit of production material is denoted by j_1, whilst the monthly inventory cost per product unit is represented by j_2. The average purchase cost for a unit of production material is symbolised as CBY_M, and the unit assembly cost of the product is denoted by l_1. The packaging cost is given by l_2, with the condition $l_2 > l_1$. Inventory quantities of production materials and finished goods assembled in advance based on forecasts are denoted by w_1 and w_2, respectively. The total product inventory is then computed as $w_1 + w_2$. Residual values for unit leftover production material and the leftover product unit are given by a_1 and a_2, respectively. Under the assumption that the product inventory quantity required during the annual peak periods H_1, H_2... is highest in the period represented by w_{MAX}, the monthly product inventory cost is reiterated as j_2. The formula for product inventory holding cost is provided in:

$$CBY_w = w_{MAX} \times j_2 \times 12 \tag{7}$$

In practical scenarios, a relationship is often observed between inventory levels and associated risks. Elevated inventory levels potentially increase risks related to capital occupancy, product obsolescence, and devaluation. This is particularly pertinent for products with limited life cycles or those sensitive to market changes. To offer a realistic representation of the impact of augmented inventory levels on overall risk, a linearly increasing risk coefficient, denoted by β, is introduced. This ensures that inventory decisions closely reflect actual operational risks. The total volume of annual product inventory is symbolised by w_{TOTAL}, and the associated risk coefficient is provided by β. The formula for inventory risk cost is formulated in:

$$CBY_{ae} = LOSS \times s \times w_{TOTAL} = (CBY_M + l_1 - a_2) \times s \times w_{TOTAL} \tag{8}$$

where, the unit loss amount $LOSS$ is calculated as $CBY_M + l_1 - a_2$.

A comprehensive cost function has been constructed, predicated on the volume of production material procurement, product output, and product inventory. This formulation reflects the multifaceted cost architecture characteristic of production and supply chain management. Incorporated within this function are the procurement costs associated with production material volumes, the production costs related to product outputs, and the combined holding and risk costs pertaining to product inventory. Simplification of this total cost function to a univariate quadratic equation concerning total demand unveils a quadratic relationship between these cost constituents. This denotes that with escalating demand, total cost exhibits a non-linear variation.

Through the differentiation of this quadratic equation and subsequent nullification of the derivative, the inflection point of the cost function is ascertainable. At a mathematical level, this juncture represents a scenario where the marginal cost equals zero, signifying that an augmentation by one unit of production material volume, product output, or product inventory ceases to increment the total cost. Given that the cost function manifests as a quadratic equation in terms of demand, the identified solution guarantees a local minimum. Resolution of this local minimum facilitates the determination of optimal values for production material volume, product output, and product inventory, anchored in the tenet of total cost minimisation. This methodological approach synergises mathematical optimisation theory with tangible production planning, offering a structured resolution to equilibrate cost and inventory risk. The attainment of this balance is critical for the augmentation of production and supply chain efficacy, enabling enterprises to uphold customer service levels whilst simultaneously curtailing operational costs and inventory risks.

4. SIMULATION RESULTS AND ANALYSIS

To rectify observed imprecisions in existing forecasting models processing complex data and apparent inflexibility in supply-demand balancing strategies, a combined ARIMA-BP neural network model was introduced. This integration seeks to amalgamate the strengths of both individual models, aiming to refine the precision of production material demand forecasting.
Simulations were conducted using the ARIMA, the BP neural network, and the combined model, with results delineated in Table I.

Table I: Simulation results of production material demand forecasting for 2021-2022.

Year	ARIMA			BP neural network			Combined model		
	Forecasted value	Error (%)	Avg. error (%)	Forecasted value	Error (%)	Avg. error (%)	Forecasted value	Error (%)	Avg. error (%)
2021	48,956	-6.45	4.75	52,348	0.13	4.56	53,248	0.33	2.18
2022	48,278	-3.15		55,368	9.12		51,236	4.23	

Forecasting errors for 2021 and 2022 generated by the ARIMA were registered at -6.45 % and -3.15 % respectively. These notable deviations highlight potential constraints in the ARIMA's capability to encapsulate the dynamic intricacies of data, especially when data portrays non-linear tendencies. In the case of the BP neural network, an error of a mere 0.13 % was recorded for 2021, which subsequently escalated to 9.12 % in 2022. The minimal error in 2021 underscores the BP network's adeptness in discerning non-linear data intricacies. Nevertheless, the heightened error in 2022 alludes to possible declines in the BP network's forecasting proficiency under specific data complexities or shifts. Contrarily, the combined ARIMA-BP neural network model yielded forecasting errors of 0.33 % on average for 2021 and 4.23 % for 2022. While the average error for 2022 remains unprovided, analysis of data from individual years intimates that the combined model consistently showcases diminished forecasting errors. It is, therefore, postulated that the amalgamated model adeptly leverages the ARIMA's linear data processing strengths and augments it with the BP neural network's prowess in pinpointing non-linear data patterns. This fusion appears to not only mitigate the inadequacies observed in singular models dealing with complex datasets but also augments overall forecasting precision.

In Fig. 4, fluctuations in forecasting errors are depicted across the ARIMA, the BP neural network, and the amalgamated ARIMA-BP version. Error magnitudes, both positive and negative percentages, signify deviations between forecasted outcomes and empirical values. A discernible observation from this graphical representation reveals inherent volatility in error magnitudes across all models, which can be attributed to the inherent variability of time series. Marked oscillations in error were evident in the ARIMA, whilst the BP neural network and the combined model demonstrated relatively stabilized results. Furthermore, forecasts generated by the combined model consistently verged closer to a zero-error mark. This observation lends weight to the notion that the integration of these models facilitates a more comprehensive grasp of both linear and non-linear time series attributes, consequently bolstering the overall fidelity of predictions.

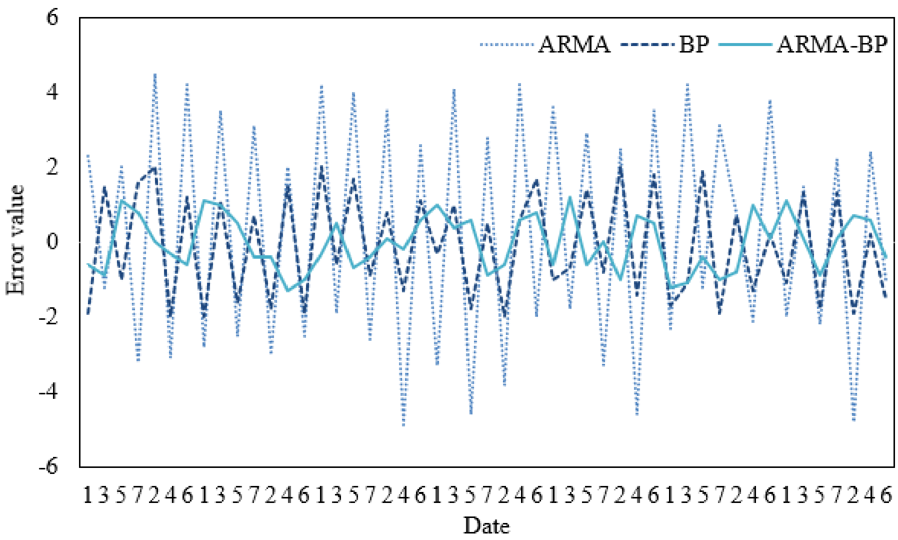

Figure 4: Comparative analysis of forecasting errors during simulation.

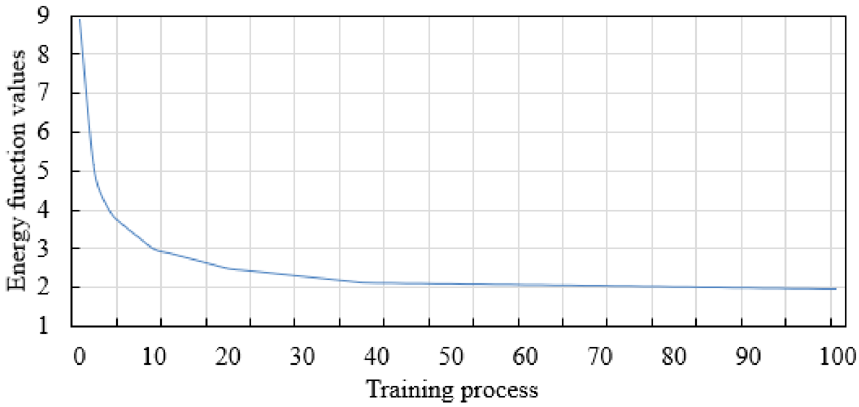

Figure 5: Energy function values of the combined forecasting model.

Fig. 5 depicts a consistent decrement in the values of the energy function throughout the iterative process. The energy function is employed as an error metric or loss function to measure the divergence between the model's present state and its training goal. A diminution in the energy function's value is indicative of progressive refinement in the model's parameters, thus enhancing the fit to the data. An expeditious descent in the energy function value is discerned during the formative stages, characteristic of the initial phases in machine learning model training where parameters typically evolve from a suboptimal forecast performance. This is followed by substantial diminutions in loss function value, owing to advancements through learning. With an increase in iterations, the rate of decline in the energy function value tapers and plateaus, signalling the model's approach toward convergence at an optimal parameter amalgamation. This evidence supports the potency of the forecast model under consideration in diminishing the energy function value through its iterative optimization process. The model's calibration of internal parameters to minimize error corroborates its forecasting proficiency, resonating with the error analysis previously articulated, and underscores the model's practical application and efficiency.

In the present study, an innovative approach to the formulation of production plans has been investigated. This approach is predicated on the balance between supply and demand, aspiring to optimize the tripartite relationship between material procurement, production output, and inventory control. Consequently, it aims to meet the twin objectives of cost management and responsiveness to market demand. Data contrasting the forecasted and actual demand values for production materials for each month of 2022 are exhibited in Table II. A comparison reveals that while the forecasts do not invariably align with exactitude, they are substantially close to the actual figures, thereby reflecting the forecast model's proficiency in tracking general demand trends. Significant discrepancies are noted for certain months, such as May and September; however, for other months like January and July, the forecasted figures notably converge with the actual data. Therefore, despite the model's inability to invariably predict exact monthly demands with perfect accuracy, it consistently provides a relatively precise overview. Such precision affords businesses the ability to implement effective procurement strategies for production materials and to manage inventory with increased efficacy. The production planning method, as explicated in this investigation and anchored on the principle of supply-demand balance, has demonstrated its effectiveness in cost containment and adaptation to market demand. It emerges as a robust managerial approach to mitigate the uncertainties and variabilities intrinsic to real-world production scenarios.

Table II: Simulated demand data for production materials in 2022 (units: pieces).

Product 2	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**
2022	31 days	28 days	31 days	30 days	31 days	30 days	31 days	31 days	30 days	31 days
Forecasted value	71,254	90,124	91,453	61,245	33,265	23,105	81,254	33,265	65,234	9,875
Actual value	68,562	91,235	92,368	57,863	32,458	31,256	78,963	30,000	70,000	6,325

Fig. 6 presents a histogram delineating two distinct datasets: capacity demand and corresponding planned production, each depicting monthly requisites and the manufacturing strategy designed to fulfil these demands, respectively. It is depicted that planned production maintains a consistent trajectory, mirroring the pattern of capacity demand, thus demonstrating an adherence of production planning to market requisites and indicating an effective synchronization between output and market needs. Notably, during months such as May, June, and November, planned production is discernibly lower than capacity demand, reflecting an inherent flexibility within the production strategy to scale down in response to diminished market demands, thereby averting excess production.

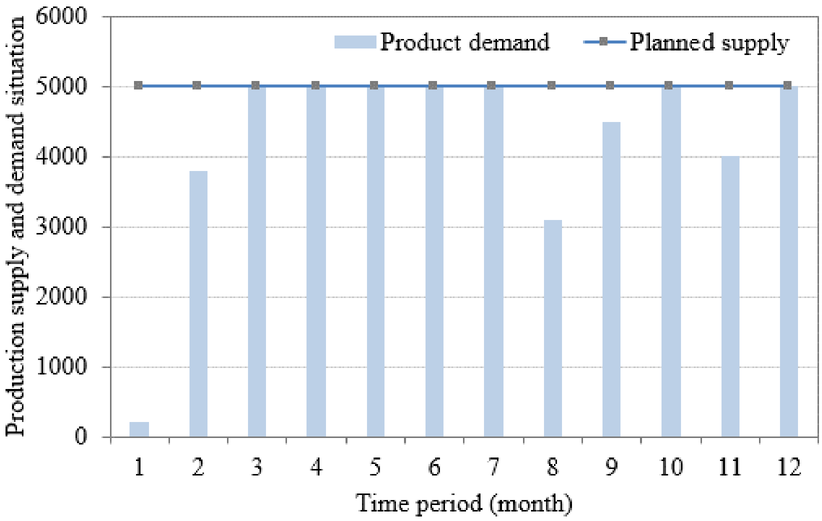

Figure 6: Histogram of production plan based on supply-demand balance.

The findings extracted from Fig. 6 advocate that the approach founded on balancing supply with demand is instrumental in maintaining congruence between capacity demand and planned production, advocating its utility in preventing surplus production and minimizing resource waste. Nevertheless, in instances where actual demand outstrips planned production, it is imperative to engage in a thorough analysis of the underlying data to ascertain the causative factors of such discrepancies, with a view to eliminate the possibility that these are the result of inefficiencies in supply chain management or forecasting errors. The histogram thus reveals a production stratagem that adeptly adjusts to market dynamics, which may contribute to a reduction in inventory overhang and an enhancement of cash flow, attesting to the method's applicability.

5. CONCLUSION

In this investigation, an in-depth analysis was conducted on a production planning methodology that emphasises supply-demand balance. The efficacy of this method has been substantiated through a series of simulations, illustrating its capability to reconcile cost management with adherence to market demand by refining the interplay of material procurement, output generation, and inventory control. Multiple forecasting models were rigorously developed and subjected to computational simulations to prognosticate the requirements for production resources. It was discovered through these simulations that a composite ARMA-BP model exhibited superior accuracy over its standalone counterparts, significantly curtailing forecasting errors. A comparative assessment of forecasted outputs against actual demands revealed the enhanced precision of the integrated approach. Nevertheless, certain temporal discrepancies were noted, highlighting the necessity for continuous refinement of forecasting methodologies.

Subsequent simulations of various production scenarios delineated the adaptability of these plans to monthly market demands. Comparative analysis delineated that strategies derived from the supply-demand balance method yielded superior alignment with demand projections. This approach has been recognised for its proficiency in managing expenditures while maintaining the agility to meet market flux. The data amassed and the resultant simulations consistently endorsed the stability, adaptability, and economic prudence of the production planning approach under review. Visual representations, such as histograms, were employed to substantiate the congruence between the planned production and actual market demands, thereby validating the proposed model's operational effectiveness.

The culmination of this research presented a model that harmonises material acquisition, manufacturing output, and inventory regulation with market demand, thereby establishing a more accurate forecasting and responsive production planning. The simulated findings endorse the presented model's capacity to minimise errors in forecasting, orchestrate judicious production schedules, navigate cost-effectively, and accommodate market variability with finesse. This study contributes a pragmatic and robust solution to the field of production management.

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