

Article

Dynamic Loss Rate Prediction for Production Materials Based on AHP-Gray Markov

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Featured Application

This work provides a lightweight, small-sample master data governance tool for SMEs in discrete manufacturing. It can be embedded into standard MRP modules to dynamically adjust material loss rates, balancing stockout risks and inventory costs without large historical datasets. Beyond the hardware and sanitary ware applications validated here, it may support long-cycle spare parts in aerospace manufacturing, cold chain replenishment for perishables, and customized furniture manufacturing with sporadic orders. By enabling accurate material planning under data-scarce conditions, it offers a practical pathway for resource-constrained manufacturers to adopt smart manufacturing with minimal IT investment.

Abstract

Accurately predicting the material loss rate is critical for MRP-driven delivery and inventory control. Inaccurate and delayed data acquisition leads to imprecise master data and poor knowledge of how machines are used in small- and medium-sized manufacturing enterprises (SMEs), but dynamic production environments and data latency are persistent challenges. This paper proposes a two-stage dynamic prediction framework integrating Time Decay Weighted Average (TDWA) and AHP-Gray Markov correction. TDWA establishes a baseline loss rate prioritizing recent process data, while the Analytic Hierarchy Process (AHP) quantifies eleven heterogeneous factors affecting material consumption. A Gray GM(1, 1) model predicts loss-rate overshoot, refined by Markov chain residual correction. Empirical validation using 42 months of production data from a hardware–sanitary ware manufacturer demonstrates a MAPE of 1.97%, outperforming standalone GM(1, 1) by 38% and the three-year average by 66.5%. The method effectively balances delivery assurance and inventory costs, maintaining zero stockouts while limiting excess inventory to 1.7%. Unlike ARIMA, XGBoost, or LSTM, which suffer from overfitting or performance degradation with eight or fewer data periods, the proposed model maintains high accuracy and robustness with extremely small samples. Offering a low-threshold “small-sample master data governance” paradigm, this approach may be applied to aerospace spare parts support, cold chain logistics, and customized manufacturing, providing a viable pathway for digital transformation in resource-constrained environments.



Academic Editor: Radu Godina

Received: 15 August 2026

Revised: 20 September 2026

Accepted: 20 September 2026

Published: 28 September 2026

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Keywords: small- and medium-sized manufacturing enterprises; material loss rate; gray GM(1,1) model; Markov residual correction; analytic hierarchy process; small sample prediction

1. Introduction

In the manufacturing industry, where BOM is the core management logic [1], the material loss rate is the key master data connecting production planning, product cost accounting, and supply chain inventory strategy [2]. Accurately predicting the material loss rate is critical for MRP-driven delivery and inventory control [3]. Inaccurate and delayed data acquisition leads to imprecise master data and poor knowledge of how machines are used in small- and medium-sized manufacturing enterprises (SMEs) [4], but dynamic production environments and data latency are persistent challenges [5]. Material availability establishes appropriate production technologies and informs the configuration of the supply chain [6]. Small- and medium-sized manufacturing enterprises have variable products and high cross-SKU material commonality [7]. Deviations in the loss rate have cascading effects as they propagate along the multi-level BOM, causing production line shutdown or excessive inventory capital occupation [8]. Despite technological evolution and changing market requirements, the basic engine used to drive information systems in ERP is still the traditional MRP system, which was developed in the 1960s [5]. In today's smart manufacturing production environment, material consumption data are often incomplete, volatile, and reflect human hesitation, making fixed parameter calculation methods insufficient to reflect the real dynamic loss characteristics of raw materials [9]. Most existing optimization literature simplifies practical operational trade-offs, pursuing numerical prediction accuracy while neglecting real-world inventory costs and stockout risks caused by rigid parameter setting [10]. If the anticipated inventory level drops below a threshold that is predefined for each material, an order is placed; there is no clear order-up-to point, which creates an incentive to over-order. If consumption unexpectedly increases, the risk of stockout is exacerbated by the long lead time [9]. Existing academic literature focuses on continuously improving this process to reduce material losses [11], and there is a lack of research on small-sample and information-poor uncertainty modeling of dynamic loss rates in BOM systems [12]. Most conventional prediction tools rely on large volumes of continuous historical data and complex algorithm structures, which impose high data collection and computing thresholds that small manufacturers cannot afford [13]. The gray system theory proposed by Deng is specifically used to deal with evolution law mining in "few data and uncertainty" systems [14]. The $GM(1, 1)$ model has been successfully applied in small-sample prediction in many fields [15], such as equipment consumption and tool wear. Markov chains are central to the understanding of random processes and can be used to model systems [16]. Combining them with $GM(1, 1)$ can effectively correct its residuals [17]. This paper introduces multi-factor gray relational analysis with AHP weighting and Gray Markov residual correction to solve the material loss rate overshoot coefficient for the first time and integrates it with a time-weighted historical average baseline to form a complete dynamic loss rate prediction method. The main contribution of this paper is to construct a dynamic loss rate prediction model that is adapted to the current data capacity of small- and medium-sized manufacturing enterprises. As a general "small-sample master data governance paradigm", it can be extended to aerospace spare parts, the fresh food cold chain, pharmaceutical logistics, and customized home furnishing [18], providing a theoretical basis and technical path for transitioning to intelligent manufacturing in a resource-constrained environment [19].

2. Materials and Methods

2.1. Time Decrease-Weighted Baseline Loss Rate

Linear ascending weight assignment for recent time periods is a reasonable smoothing strategy for trending time series, since newly generated data contain more real-time information and better reflect the system's current operating status, while older data are discarded

to eliminate the interference of obsolete production conditions [20]. A time-decay weighted average is used to calculate the baseline loss rate WS_{bas} [21]. Let WS_k be the average loss rate of the k_{th} month ($k = 1$ is the earliest month). The weight ω_k increases linearly as time approaches the present.

$$\omega_k = \frac{2k}{i(i+1)}, WS_{bas} = \sum_{k=1}^i \omega_k \times WS_k$$

New materials are replaced by materials with similar process routes and specifications, and only data from the past 38 months are adopted to eliminate interference from outdated processes.

2.2. AHP Determines the Weights of Factors Affecting the Correction Coefficient

AHP is useful for determining the relative weight of each criterion [22] and uses nine levels of importance, which are listed in Table 1. Hierarchical structures evaluated with AHP take the form of a central question that has several choices, each of which is judged against different criteria. Evaluators initially rank the importance of each factor based on experience and then calculate their weights [23]. Table 1 shows all the 11 factors. Table 2 shows the scale value of each factor.

Eleven factors affecting the over-excess correction coefficient of the loss rate were selected by expert review using the Delphi method.

Table 1. List of factors affecting the over-excess coefficient.

No	Factor	Meaning
F1	Material cost	Risk of excess inventory tying up capital
F2	Acquisition time	Time from placing a purchase order to receiving the materials
F3	Shareability	Cross-SKU capacity to process excess materials
F4	Storage costs	Special storage conditions and volume
F5	Storage lifespan	Risk of spoilage/expiration and disposal
F6	Order continuity	Subsequent demand absorbs excess capacity
F7	Customer importance	Penalty for delayed delivery/loss of reputation
F8	Product grade requirements	Current order tolerance stringency
F9	Current management quality	Quality control stability and data reliability
F10	Downstream production processes	Depreciation of the reference value of historical data
F11	Changes in downstream production staff	Fluctuations in operational skill

A matrix formed by pairwise comparisons is called a judgment matrix and has the following properties: $a_{ij} = \frac{1}{a_{ji}}$. Experts constructed an 11th-order judgment matrix through pairwise comparisons [24].

Table 2. Scaling table of the judgment matrix a_{ij} .

The Importance of Factor i Compared to Factor j	Scale Value
Equally important	1
Slightly more important	3
Obviously more important	5
Intensely more important	7
Extremely important	9
The median value between two adjacent judgments	2, 4, 6, 8

Note: The ratio of the importance of factor i to factor j is a_{ij} , and the ratio of the importance of factor j to factor i is $a_{ji} = 1/a_{ij}$.

The pairwise comparison matrix was aggregated from multiple expert judgments via the Delphi-AHP procedure. A panel of 7 domain experts with 6–14 years of work experience in discrete manufacturing material management participated, including purchasing supervisors, MRP operators, and senior production supervisors. Two Delphi rounds were implemented. In Round 1, each expert independently completed an 11-dimensional pairwise comparison judgment matrix. In Round 2, anonymized aggregated results from Round 1 were fed back, and experts revised their judgments. The consensus stopping criterion was set at $\geq 80\%$ agreement on factor importance rankings among experts. Individual matrices were aggregated using the geometric mean method to generate the final group-level judgment matrix shown in Table 3. The consistency test yielded a $CR = 0.0197 < 0.1$.

The normalized weight vector was calculated as $W = [\omega_1, \dots, \omega_{11}]^T$ and the consistency test yielded $CR = 0.0197 < 0.1$, indicating that the judgment matrix had satisfactory consistency. The results are as follows:

Influencing Factors:	Material cost	Acquisition duration	Part commonality	Storage Cost	Storable time	Order Sustainability	Customer Weight	Output Grade Requirements	Current Management Level	Downstream Process Changes	Back-end Staff Turnover
Weight W:	0.0360	0.0980	0.1420	0.0580	0.0997	0.0940	0.0987	0.0967	0.0980	0.0964	0.0820

Radial basis function neural networks (RBFNs) have been successfully used in various fields, including pattern recognition and classification tasks [25,26].

The weighted comprehensive score of the material calculation factors for each period is set as follows k : the comprehensive score for the period is $S(k) = \sum \omega_j \cdot s_j(k)$, and the range standardization is obtained as $S'(k) = \frac{S(k) - S_{\min}}{S_{\max} - S_{\min}}$. The linear relationship between $S(k)$ and $c^0(k)$ is established by least squares fitting $S'(k)$: $c^0(k) = \alpha S'(k) + \beta$, thereby transforming the multi-factor score into a correction coefficient sequence that can be directly used for GM modeling and aligning it with the historically ideal correction coefficient sequence as the input for gray modeling.

The ideal overshoot correction factor for period i is $c^0(i, k) = \frac{WS_{ideal}(i, k)}{WS_{bas}(i, k)}$, where $WS_{ideal}(i, k)$ is the ideal loss rate assessed by experts for period (i, k) , and $WS_{bas}(i, k)$ is the baseline loss rate calculated by TDWA for the same period. This factor reflects the loss rate magnification factor required to balance material shortage risk and inventory cost under specific production conditions.

Table 3. Pairwise comparison scores of factors affecting the over-excess coefficient.

		1	2	3	4	5	6	7	8	9	10	11
		Material Cost	Acquisition Duration	Part Commonality	Storage Cost	Storable Time	Order Sustainability	Customer Weight	Output Grade Requirements	Current Management Level	Downstream Process Changes	Back-End Staff Turnover
1	Material cost	1	1/3	1/8	1/2	1/5	1/7	1/5	1/7	1/6	1/4	1/3
2	Acquisition duration	3	1	1/3	1	1/2	1/3	1/2	1/3	1/2	1	1
3	Part commonality	8	3	1	5	2	1	2	1	2	2	3
4	Storage Cost	2	1	1/5	1	1/3	1/4	1/2	1/3	1/3	1/2	1/2
5	Storable time	5	2	1/2	3	1	1/2	1	1	1	1	2
6	Order Sustainability	7	3	1	4	2	1	2	2	2	3	3
7	Customer Weight	5	2	1/2	2	1	1/2	1	1	1	2	3
8	Output Grade Requirements	7	3	1	3	1	1/2	1	1	1	2	3
9	Current Management Level	6	2	1/2	3	1	1/2	1	1	1	2	3
10	Downstream Process Changes	4	1	1/2	2	1	1/3	1/2	1/2	1/2	1	2
11	Back-end Staff Turnover	3	1	1/3	2	1/2	1/3	1/3	1/3	1/3	1/2	1

2.3. GM(1,1) Baseline of Gray Model Prediction Correction Coefficient [27]

The original sequences of ideal overshoot correction coefficients from various historical periods are taken, and the trends in their monotonic evolution are explored using gray theory. Specific modeling steps include cumulative generation (AGO), establishing the whitening differential equation, and solving for the parameter vector:

$$C^0 = \{c^{(0)}(1), c^{(0)}(2), \dots, c^{(0)}(n)\}, n \geq 4$$

Step 1—1-AGO cumulative generation:

$$c^{(1)}(k) = \sum_{i=1}^k c^{(0)}(i), k = 1, 2, \dots, n$$

Step 2—The whitening differential equation is established:

$$\frac{dc^{(1)}}{dt} + ac^{(1)} = b$$

The parameter vector $[a, b]^T$ is solved using the least-squares method:

$$[a, b]^T = (B^T B)^{-1} B^T Y$$

$$B = \begin{bmatrix} -\frac{1}{2}[c^{(1)}(1) + c^{(1)}(2)] & 1 \\ -\frac{1}{2}[c^{(1)}(2) + c^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[c^{(1)}(n-1) + c^{(1)}(n)] & 1 \end{bmatrix}, Y = [c^{(0)}(2), c^{(0)}(3), \dots, c^{(0)}(n)]^T$$

Step 3—Time response function and accumulation restoration:

$$\hat{c}^{(1)}(k+1) = \left(c^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}$$

$$\hat{c}^{(0)}(k+1) = \hat{c}^{(1)}(k+1) - \hat{c}^{(1)}(k), k = 1, 2, \dots, n-1$$

$\hat{c}^{(0)}(k)$ This is the preliminary predicted value of the correction coefficient given by GM(1,1).

2.4. Markov Chain Residual Correction [28]

To capture the random fluctuations in the production environment, Markov corrections were performed on the residual sequence of the GM (1,1) model. The residual sequence is partitioned into $m = 3$ states by quantile segmentation: negative-bias state E_1 , normal state E_2 , and positive-bias state E_3 .

Step 1—Residual Sequence:

$$\varepsilon(k) = c^0(k) - \hat{c}^{(0)}(k), k = 2, \dots, n.$$

Step 2—State Division: The residual series is divided into three states according to the lower quartile and upper quartile of the residuals. E_1 (negative-bias): residual < lower quartile; E_2 (normal): lower quartile $\leq$ residual $\leq$ upper quartile; E_3 (positive-bias): residual > upper quartile. The frequency of each state transition is counted to obtain the transition probability $P = (p_{ij})$ matrix [29]:

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^m n_{ij}}$$

where n_{ij} is the frequency of transitions from state E_i to state E_j .

Step 3—Residual Compensation: For the predicted time $k+1$, given current residual state E_i , the most probable transition state E_j is obtained from transition matrix P. The

midpoint value ε_j of state- j interval is adopted for residual compensation. $\hat{c}^{(0)}(k+1)$ P the most likely transition state E_j is found from the given state E_i , and the midpoint E_j of the interval $\bar{\varepsilon}_j$ is used for correction.

$$E_{i_{corrected}}^0(k+1) = \hat{c}^{(0)}(k+1) + \bar{\varepsilon}_j.$$

2.5. Synthesis of Dynamic Loss Rates

The final dynamic material loss rate is

$$WS_{dyn} = WS_{bas} \times \tilde{c}^{(0)}(k+1).$$

Among these $\tilde{c}^{(0)}(k+1) \in [1.00, 1.15]$, it is necessary to ensure reasonable over-profit while avoiding uncontrolled over-profitability.

3. Empirical Verification

3.1. Expert Assessment of Ideal Loss Rate

The ideal loss rate according to expert evaluation in the following section was determined using a retrospective triangulation method. The three evaluators for ground truth assessment—a process engineer, supply chain manager, and planning manager—were completely independent of the Delphi-AHP expert panel and did not participate in model construction or AHP weighting. These evaluators independently conducted retrospective evaluations based on current production logs (work order reporting data, quality inspection records, and return slips) and determined the material loss rate that should be expected for MRP under actual monthly production conditions. The median of the three evaluation results was taken as the ideal loss rate for expert evaluation. Outliers induced by one-off exogenous shocks such as occasional equipment failures and temporary power outages were removed when calibrating the ideal loss rate under regular operating conditions. Note: such exogenous disruptions represent real-world operational uncertainty; future research may retain these outliers to test model performance against unforeseen disturbances. This processing method removes random noise, retains the true signal reflecting material properties and management capabilities, and ensures the objectivity of the evaluation benchmark. All ground truth assessments were completed without accessing test-set data to avoid data leakage.

3.2. Data and Settings

Production records spanning 42 consecutive months were collected for 25 typical materials from a hardware–sanitary ware manufacturer, consisting of 12 low-waste items with a loss rate below 2.5% and 13 high-waste items with a loss rate equal to or above 2.5%. The first 38 periods ($n = 38$) for each material were adopted to establish the GM(1, 1) model, while the subsequent four-period dataset was used for model testing. The number of states for the Markov chain was set as $m = 3$, corresponding to negative deviation, normal condition, and positive deviation. The theoretically ideal loss rate obtained via expert evaluation was taken as the benchmark true value.

To ensure a fair comparison, all models were trained using data from the first 38 periods and tested using data from the last 4 periods. Given the small sample size, the baseline model parameters were set to suppress overfitting.

(1) ARIMA model. Grid search was used to find the minimum AIC within the range. $p \in \{0, 1, 2\}$, $d \in \{0, 1\}$, $q \in \{0, 1, 2\}$. The maximum model order was restricted to (2,1,2) to avoid a sharp increase in the variance of parameter estimation with a small sample size, and to prevent the model from capturing random noise rather than the true trend.

(2) XGBoost model. The configuration was $\text{max_depth} = 3$, $\text{learning_rate} = 0.05$, $\text{subsample} = 0.8$, $\text{reg_alpha} = 0.5$. Five-fold inner cross-validation on the training data

was applied to select optimal boosting rounds. Strong regularization and a shallow tree structure were used to offset the sensitivity of ensemble learning to small samples.

(3) LSTM model. It was configured as a single layer with 50 neurons, Dropout = 0.3, and Batch Size = 2. Adam optimizer. Early stopping based on training loss was implemented to mitigate overfitting. Mini-batch training was intended to alleviate the scarcity of data, but because recurrent neural networks have extremely high requirements for sample size, the results were mainly used as a reference.

3.3. Comparison of Loss Rate Performance Obtained Using Seven Methods

The MAPE of the Gray Markov method is 1.97%, which is about 38% lower than that of pure GM(1,1) and 66.5% higher than the three-year simple average, as Figure 1. The dynamic loss rate for key customer materials with long lead times is moderately increased to avoid the hidden material shortage risk caused by the historical average. High-cost general materials are not excessively amplified, and the excess inventory rate is controlled at 1.7%, as Figure 2.

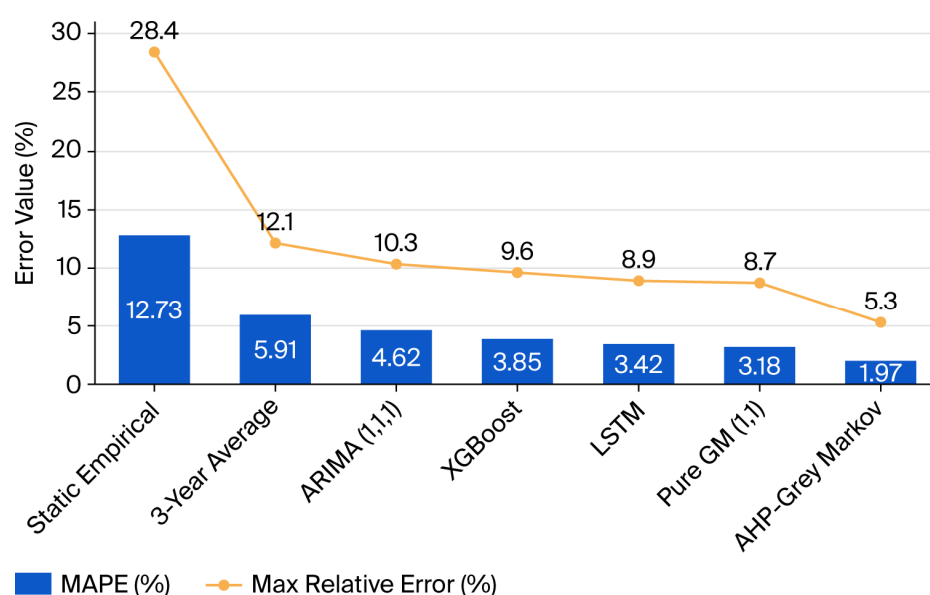


Figure 1. Prediction accuracy comparison (MAPE vs. Max Relative Error).

Retrospective MRP Simulation for Business KPIs

The reported annual stockout times and average inventory surplus are outputs from a retrospective MRP simulation instead of real-world on-site implementation. Key simulation settings are given below:

1. Demand input: Real monthly gross material demand derived from production orders from the manufacturer.
2. MRP replenishment logic:

$$\text{Net_requirement} = \text{Gross_requirement} - \text{Available_inventory}$$

$$\text{Planned_order_quantity} = \text{Gross_requirement} \times \text{Dynamic_material_loss_rate}$$
3. Lead time: Actual procurement lead time for each material recorded in the enterprise ERP.
4. KPI definitions: Annual stockout stops refer to the number of months when on-hand inventory cannot satisfy net material requirement. The excess inventory rate is the average proportion of ending inventory that exceeds the actual consumption requirement. Simulation outcomes (zero stockouts, 1.7% excess inventory) hold only for this historical dataset; practical deployment may deviate under real-world supply disruptions.

ARIMA is prone to overfitting with small sample sizes and lags in its response to mutations, and XGBoost/LSTM perform close to Gray Markov with ≥ 20 periods of data,

but their generalization ability decreases with ≤ 8 periods of data. The proposed method maintains the highest accuracy and optimal inventory/delivery balance with extremely small sample sizes.

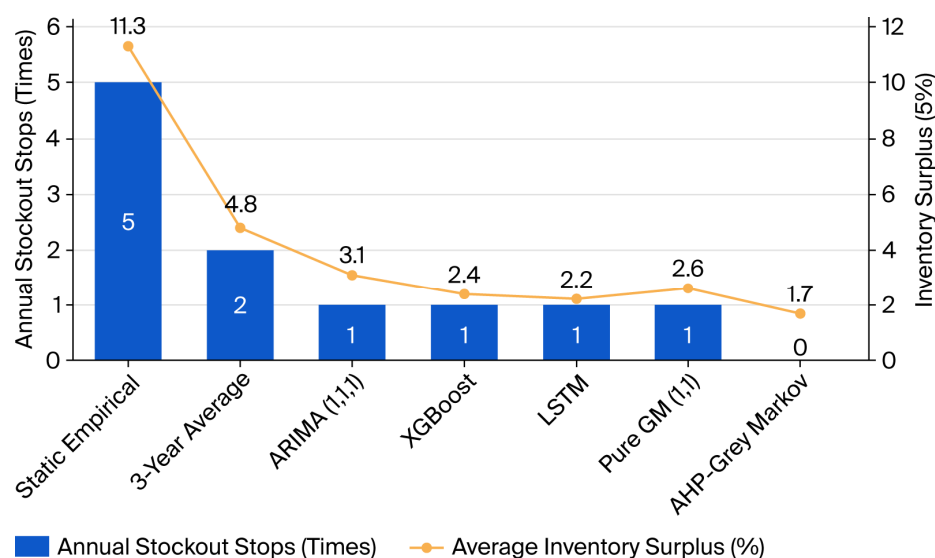


Figure 2. Business performance comparison (Stockout vs. Inventory Surplus).

3.4. Comparison of the Accuracy and Robustness of Five Models

Figure 3 illustrates the performance of five models and two lots in predicting the actual material loss rate based on 42 months of production data. The static empirical and three-year average methods show the most notable deviations, as their constant values fail to track the gradual upward and fluctuating trend of actual loss rates. ARIMA, XGBoost, and LSTM deliver moderate accuracy but show limited performance with 38 training periods. The pure GM (1,1) model outperforms these conventional approaches, while the proposed AHP-Gray Markov model produces the predictions that are most consistent with actual values, verifying its superior fitting capacity and robustness in small-sample dynamic prediction.

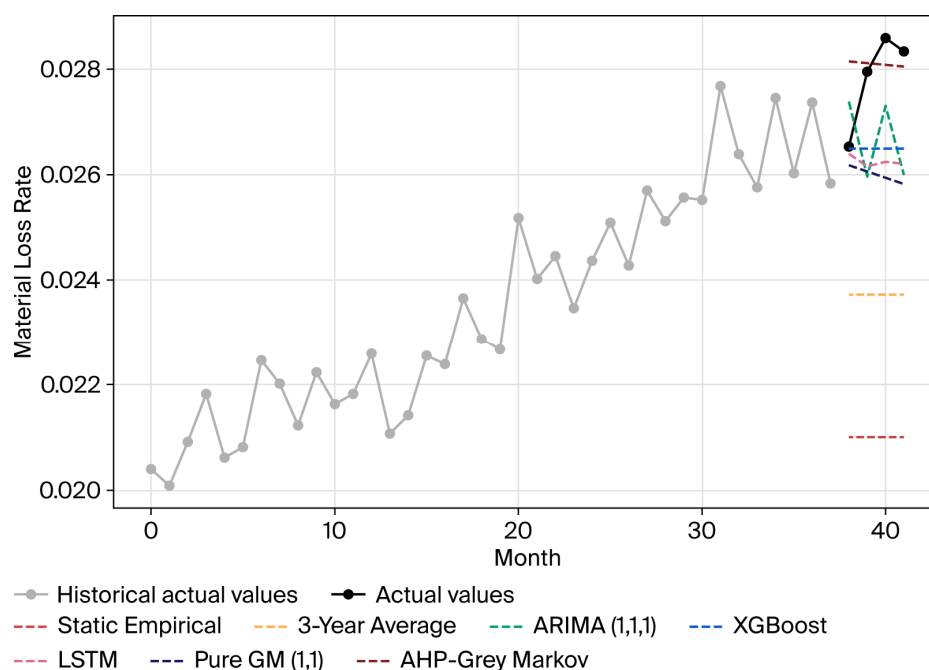


Figure 3. Comparison of loss rate predictions across models.

The comparison shows that the AHP-Gray Markov model is better than ARIMA, XGBoost, and LSTM GM(1,1) in terms of prediction accuracy, robustness to small samples, inventory optimization, and delivery assurance. Although its computational complexity is slightly higher than that of ARIMA and XGBoost, it achieves the best balance between accuracy and feasibility using extremely small samples, as Figure 4.

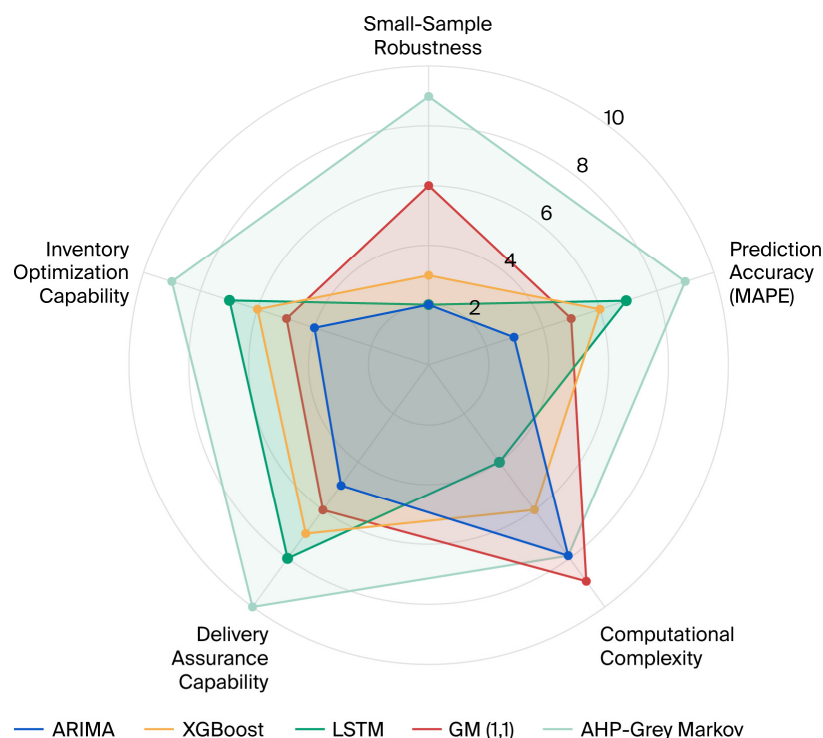


Figure 4. Radar chart comparing the accuracy and robustness of different models.

4. Discussion

4.1. Theoretical Contributions and Mechanism Advantages

The AHP-Gray Markov framework constructed in this study is essentially a hybrid modeling paradigm for uncertain systems with limited information. It effectively integrates “cognitive uncertainty” (expert experience) and “stochastic uncertainty” (production fluctuations). By utilizing gray theory to mine the monotonic evolution trend of limited data, the model avoids the large-sample dependence and overfitting risk of ARIMA and deep learning with only eight training periods. By introducing Markov chains to perform probabilistic calibration of residuals and combining AHP multi-factor weight mapping, it moves from “simple time series prediction” to “factor-driven prediction”.

4.2. Practical Value and Significance for Promotion

Empirical results show that the method effectively balances delivery assurance and cost control. Its greatest practical advantage lies in its low implementation threshold: it does not require large-scale historical data and can be embedded into a standard MRP module using only conventional matrix operations, which is of value for resource-constrained small- and medium-sized enterprises. Based on this, the logic of “small-sample master data governance” has potential for future application to industries with high uncertainty and low data density. These cross-domain applications have not been empirically validated in the present work and require further independent research. For example, prospective applications include supporting aerospace spare parts for long-cycle low-consumption

components, dynamic replenishment for perishable goods in fresh cold chain logistics, and precise material planning for customized discrete manufacturing with sporadic orders.

4.3. Limitations and Future Work

Despite its excellent performance, this framework still has limitations: determining AHP weights depends on expert experience [30]. Although it has undergone the Delphi method and passed the consistency test, it still requires human intervention when facing a completely new process route. Future work will focus on introducing a metabolic mechanism to perform online rolling updates of gray model parameters and exploring the optimization of Markov state partitioning through fuzzy logic, so as to further reduce the model's subjective dependence on human experience. In addition, although we performed weight perturbation sensitivity tests in Supplementary Material, expert-driven AHP weighting still introduces subjective dependence, especially for completely new production routes without historical reference.

5. Conclusions

To address the common challenges faced by small- and medium-sized manufacturing enterprises, such as scarce historical data, incomplete information, and rigid traditional loss rate evaluation methods, this paper proposes a two-stage dynamic prediction framework that integrates a time-decay-weighted average (TDWA) baseline with AHP-Gray GM(1, 1) Markov residual correction. An empirical analysis of 42 months of production data for 25 typical materials from a hardware and sanitary ware manufacturing company was used to verify the effectiveness and superiority of the proposed method.

First, the framework demonstrates excellent prediction accuracy with extremely low sample sizes ($n = 38$). By introducing a Markov chain to perform probabilistic correction of residuals, the single gray model's limited adaptability to random fluctuations is effectively overcome, reducing the MAPE to 1.97%, which is 66.5% higher than that of the three-year simple averaging method and about 38% higher than that of the pure GM(1, 1).

Secondly, the dynamic loss rate mechanism balances delivery assurance and inventory costs. Using adaptive adjustments based on material properties and supply risks, it avoided any material shortages or production line stoppages throughout the empirical period and controlled the excess inventory rate at 1.7%, addressing the hidden material shortages and capital backlog caused by the traditional "one-size-fits-all" approach.

Finally, compared to ARIMA and deep learning models, which rely on large samples, lightweight hybrid forecasting models without high data demands are better suited to act as master data governance tools for intelligent manufacturing in resource-restricted small manufacturers, and can be embedded into MRP systems using only conventional matrix operations, making them highly practical for engineering applications. The logic of "small-sample master data governance" exhibits prospective potential for future migration to industries with high uncertainty and low data density. These cross-domain applications have not been empirically validated in the present work and require further independent research. For example, prospective applications include aerospace spare parts support for long-cycle low-consumption components, dynamic replenishment for perishable goods in fresh cold chain logistics, and precise material planning for customized discrete manufacturing with sporadic orders.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16199609/s1>.

Author Contributions: Conceptualization, H.M., C.L. and X.W.; methodology, H.M.; software, H.M.; validation, H.M.; formal analysis, H.M.; investigation, H.M.; resources, H.M.; data curation, H.M.;

writing—original draft preparation, H.M.; writing—review and editing, H.M.; visualization, H.M.; supervision, C.L. and X.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: All the authors declare no conflict of interest.

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