

Integrating DEA and Grey Methods for Autonomous Maintenance in Mobile Phone Production

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Abstract

In recent years, the mobile phone manufacturing industry has advanced rapidly in over the world, led by major technology firms such as Samsung Electronics. This study employs Data Envelopment Analysis (DEA) together with Grey theory to build a Total Productive Maintenance (TPM) framework integrated with an Autonomous Maintenance strategy for optimizing the mobile phone production system. The model enables systematic evaluation, monitoring and forecasting of performance at each production stage, allowing managers to detect bottlenecks and prioritize timely improvements that raise operational efficiency and reduce unexpected downtime. Results indicate that the integrated approach delivers stable gains in productivity while minimizing waste, defects and idle time across the line. Data-driven insights highlight practical solutions in equipment maintenance, workforce utilization, material flow, quality control and process optimization. Implementing Autonomous Maintenance also strengthens operator responsibility, improves technical skills, enhances teamwork and sustains consistent product quality over long production cycles. Beyond factory performance, the framework supports long-term competitiveness, cost reduction, operational resilience and sustainable development in the mobile phone sector. Overall, this research demonstrates how combining DEA and Grey analysis within TPM provides a reliable pathway for continuous improvement, smarter decision-making and meaningful economic contribution at both national and global levels, strongly supporting industrial modernization worldwide.

Keywords: Autonomous Maintenance, DEA, Grey Forecasting, Malmquist Index, Production Efficiency, TPM.

Introduction

The electronics manufacturing industry has grown rapidly, becoming a key global economic driver. Smart devices, particularly mobile phones, play a fundamental role in modern technological development, significantly contributing to digital transformation and industrial sustainability (1, 2). With intensifying consumer expectations for advanced features, shorter lifecycles and flawless quality, manufacturers face immense pressure to optimize operations. In Vietnam, this sector substantially boosts export value and economic growth, driven by multinational corporations like Samsung Electronics (3-5). Establishing these mega-facilities transforms regional supply chains, demanding unparalleled operational excellence. Given the increasing complexity of manufacturing systems, improving production efficiency and maintaining stability are critical challenges. Mobile phone production requires high precision, continuous operation and effective maintenance to ensure quality and reduce downtime. Unforeseen mechanical failures or process inefficiencies in

these high-throughput environments cause massive financial losses, material waste and disrupted delivery schedules. Consequently, achieving continuous, uninterrupted production is a strategic imperative, prompting the development of various analytical optimization methods. To address these complexities, numerous studies have explored analytical methods. DEA is widely used to evaluate the relative efficiency of decision-making units (DMUs) based on multiple input and output variables (6, 7). Research demonstrates that DEA identifies inefficient units and provides robust mathematical benchmarks for performance improvement, allowing managers to trim excess labor or material inputs. Concurrently, Grey system theory effectively forecasts situations with limited or uncertain data, common in real-world industrial systems (8-10). Studies leveraging the GM (1,1) model report highly accurate predictions of equipment degradation and production yields, even with sparse historical datasets. Maintenance strategies also crucially improve manufacturing

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performance. TPM, particularly autonomous maintenance (AM), effectively enhances equipment reliability, reduces unexpected failures and improves overall equipment effectiveness (11-14). Empowering operators through AM significantly decreases minor stoppages and defect rates, supporting the transition toward smart manufacturing systems.

Despite documented successes, these methodologies possess distinct limitations when applied independently. DEA's primary limitation is its deterministic, backward-looking nature; it evaluates historical performance without anticipating future inefficiencies. Conversely, Grey forecasting excels at predicting future states but cannot benchmark the relative efficiency of those states against other units. Furthermore, traditional TPM and AM frameworks are typically implemented qualitatively, relying on rigid, time-based schedules or generic guidelines. They lack the quantitative, data-driven rigor required to dynamically prioritize maintenance tasks based on mathematical performance degradation.

Most existing studies apply DEA, Grey forecasting and TPM independently, leaving a critical lack of comprehensive frameworks integrating historical efficiency evaluation, future prediction and proactive maintenance decision-making. This limits manufacturers' proactive responses to system inefficiencies. Without a cohesive model linking mathematical efficiency scores to shop-floor maintenance actions, plant managers operate in data silos. This disconnect frequently results in maintenance resources being spread too thin or allocated to healthy machines, while stressed equipment is overlooked until a catastrophic failure occurs.

This study addresses this gap by proposing an integrated DEA-Grey framework within a TPM-Autonomous Maintenance context for mobile phone production. The overarching aim is to develop and validate a closed-loop, data-driven methodology translating quantitative performance assessments into predictive maintenance execution. By directly embedding operators into the analytical feedback loop, this approach ensures that theoretical predictions are seamlessly converted into practical, shop-floor interventions. The main contribution is a hybrid framework integrating DEA and Grey forecasting for efficiency evaluation, performance prediction and

maintenance decision-making under uncertainty. The study pursues four specific objectives:

- (a) systematically measuring historical operational efficiency using a robust DEA model to identify bottlenecks;
- (b) applying the Grey GM (1,1) model to predict future production variables based on limited data;
- (c) projecting future efficiency scores by feeding Grey-forecasted data back into the DEA model; and
- (d) establishing a structured autonomous maintenance workflow that utilizes these predictive scores to dynamically allocate maintenance tasks, proactively preventing breakdowns.

The combination of DEA and Grey theories rests on highly complementary strengths. DEA provides a robust multi-criteria efficiency baseline but cannot predict future states. Grey theory excels at accurate forecasting with small datasets but cannot evaluate relative efficiency. Their combination creates a synergistic closed-loop system where grey forecasting predicts future variables and DEA translates those forecasts into future efficiency scores. This hybrid is theoretically superior to optimization approaches like machine learning (ML) predictive models. While ML requires vast big data and computational power, the DEA-Grey framework functions effectively as a small data solution (3). It requires minimal historical data and provides highly interpretable results, making it highly practical for rapid decision-making in dynamic manufacturing. Furthermore, this adaptability allows small and medium enterprises within the broader electronics supply chain to adopt the framework without requiring prohibitive investments.

The novelty of this study lies in its methodological hybridization and direct practical application to electronics manufacturing. This research bridges the gap between operations research DEA/Grey theory and industrial maintenance engineering (TPM/AM). By transforming backward-looking efficiency scores into actionable maintenance directives, the framework acts as a virtual sensor. It enables manufacturers to predict equipment degradation and optimize schedules without expensive physical sensors or complex infrastructures (2). This creates a highly cost-effective tool that elevates Autonomous Maintenance from a routine schedule to a

mathematically optimized, predictive strategy, offering a fresh perspective on sustaining high-yield mobile phone production.

Methodology

Data Collection and Software Tools

To ensure robust empirical analysis, data was meticulously collected from the mobile phone production system of Samsung Electronics. The observation period spans 20 consecutive years (2005 to 2024), yielding an annual longitudinal dataset. The sample size consists of aggregate data representing the main smartphone assembly lines within the facility.

Data sources included internal enterprise resource planning databases, manufacturing execution systems and official annual corporate reports. The frequency of data collection was aggregated on a yearly basis to align with long-term strategic maintenance planning. Prior to analysis, preprocessing and cleaning procedures were applied: missing values were addressed using linear interpolation and monetary values were normalized to account for inflation, ensuring consistency across the two-decade timeline.

To improve the reproducibility of this research, specific software packages and computational tools were employed. DEA was used to implement the DEA Super-SBM models and calculate Malmquist indices (15-17). MATLAB was utilized to program the Grey GM (1,1) forecasting algorithms (18-20) and calculate error metrics, while statistics 26 was used for descriptive statistics and correlation matrix generation.

Decision Making Units and Variable Selection

In this study, the DMUs are defined as the discrete operational years (2005 to 2024) of the mobile phone production system. This definition is highly suitable because each year operates as a distinct managerial period facing specific input constraints and aiming for maximum output targets, allowing for a longitudinal benchmarking of how

production efficiency and maintenance effectiveness evolve over time.

A robust theoretical and practical justification is applied to the choice of input and output variables for the DEA model. On the input side, three variables were chosen: Labor, input materials and electricity consumption. Electricity is a crucial practical indicator because deteriorating equipment with high mechanical friction consumes significantly more power; thus, energy use directly relates production efficiency to maintenance performance. On the output side, standard output and estimated revenue were selected. Together, these indicators comprehensively measure how well the system converts operational and maintenance resources into profitable yields.

The Data Envelopment Analysis

Methodology

The group applied the DEA method, focusing on problem formulation, to measure and improve production and management efficiency at Samsung Electronics' Company (21). The specific DEA model employed in this manuscript is the output-oriented Super-SBM model (22, 23). The model operates under the assumption of variable returns to scale, recognizing that modern electronic manufacturing plants often operate at suboptimal scales due to fluctuating global market demands and supply chain constraints. The output-oriented approach is chosen because the primary goal of the factory is to maximize production output and revenue from a given set of fixed inputs that includes the labor, equipment, facilities which is rather than downsizing the inputs.

Furthermore, the DEA model is fundamentally based on several assumptions: Isotonicity, homogeneity of DMUs and the absence of measurement errors. A known limitation related to these assumptions is that DEA is a deterministic technique; it does not inherently account for statistical noise, making the preprocessing of data highly critical.

The general form of the SBM model is expressed as Equation [1] (24):

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / x_{i0}}{1 + \frac{1}{s} \sum_{i=1}^s s_i^- / y_{i0}} \quad [1]$$

The best-performing units, which operate under full efficiency, are represented by unity (1.0) in all DMUs. The Super-SBM model was developed based on the conventional SBM model. Recent study

discusses that these efficient DMUs were distinguished and ranked using the Super-SBM model (22).

If a DMU is SBM-efficient, the Super-SBM model is expressed as Equations [2] and [3] :

$$\min \delta = \frac{\frac{1}{n} \sum_{i=1}^m \bar{x}_i / x_{i0}}{\frac{1}{s} \sum_{r=1}^s \bar{y}_r / y_{r0}} \quad [2]$$

$$\text{s.t } \bar{x} \geq \sum_{j=1, \neq 0}^n \lambda_j x_j, \bar{y} \leq \sum_{j=1, \neq 0}^n \lambda_j x_j, \bar{y} \geq x_0 \text{ and } \bar{y} \leq y_0, \bar{y} \bar{y} \geq y_0, \lambda \geq 0. \quad [3]$$

Similar to other DEA models, addressing negative output values and assessing the efficiency of the SBM model are both crucial considerations. However, negative data can still play a legitimate role in measuring efficiency, as a new framework

has been introduced in the DEA to handle such cases. The following diagram presents the modified framework.

Suppose $y_{r0} \leq 0$. We determine $\bar{y}_r^+$ and y_{-r}^+ as expressed in Equations [4] and [5]:

$$\bar{y}_r^+ = \max_{j=1, \dots, n} \{y_{rj} | y_{rj} > 0\} \quad [4]$$

$$y_{-r}^+ = \min_{j=1, \dots, n} \{y_{rj} | y_{rj} > 0\} \quad [5]$$

If the output r does not have a position element, Formally, it is expressed as: $\bar{y}_r^+ = y_{-r}^+ = 1$. This component is substituted with s_r^+ / y_{r0} in the target function and the value y_{r0} the constraints is not modified any circumstances.

If $\bar{y}_r^+ > y_{-r}^+$ this term is expressed as Equation [6]:

$$s_r^+ / \frac{y_{-r}^+ (\bar{y}_r^+ - y_{-r}^+)}{\bar{y}_r^+ - y_{r0}} \quad [6]$$

If $\bar{y}_r^+ = y_{-r}^+$ this term is expressed as Equation [7]:

$$s_r^+ / \frac{(y_{-r}^+)^2}{(\bar{y}_r^+ - y_{r0})} \quad [7]$$

In DEA solver, ($B = 100$), where B is a large positive number. In all cases, the denominator is positive and strictly smaller. Moreover, it is inversely proportional to the distance. Therefore, this framework reflects the degree of positivity of non-positive outputs.

Productivity Index – Malmquist

Productivity Index

The Malmquist Index evaluates the efficiency change of a DMU over a specific period. The

Malmquist Productivity Index (MPI) was introduced and defined as the product of two components: the catch-up effect and the frontier-shift effect. The catch-up term, also known as efficiency change, reflects the effort of each helping the DMU achieve a higher efficiency score with respect to the benchmark frontier. Meanwhile, the frontier-shift term represents the change in the efficiency frontier of the DMU between two time periods, t_1 and t_2 .

Now, we denote the efficiency score of a DMU measured using the frontier technology at time t_2 as expressed in Equation [8] (15-17):

$$\delta^{t2}((x_0, y_0)^{t1}), (t_1=1, 2 \text{ và } t_2=1, 2) \quad [8]$$

Using this notation, the catch-up effect can be expressed as Equation [9]:

$$\text{Catch - up} = \frac{\delta^{t2}((x_0, y_0)^{t2})}{\delta^{t1}((x_0, y_0)^{t1})} \quad [9]$$

The frontier-shift effect is represented as Equation [10] (16, 17):

$$\text{Frontier - shift} = \left[\frac{\delta^{t1}((x_0, y_0)^{t1})}{\delta^{t2}((x_0, y_0)^{t1})} \times \frac{\delta^{t1}((x_0, y_0)^{t2})}{\delta^{t2}((x_0, y_0)^{t2})} \right]^{\frac{1}{2}} \quad [10]$$

The MI is derived by multiplying the catch-up effect with the frontier-shift effect. This index is typically expressed in multiplicative form and its mathematical representation is given by Equation [11] (15):

$$\text{MI} = \left[\frac{\delta^{t1}((x_0, y_0)^{t2})}{\delta^{t1}((x_0, y_0)^{t1})} \times \frac{\delta^{t2}((x_0, y_0)^{t2})}{\delta^{t2}((x_0, y_0)^{t1})} \right]^{\frac{1}{2}} \quad [11]$$

If $\text{MI} > 1$, it indicates that the DMUo has achieved total factor productivity growth from period t_1 and t_2 , while $\text{MI} = 1$ indicates no change and $\text{MI} < 1$, reflects a decline in total factor productivity.

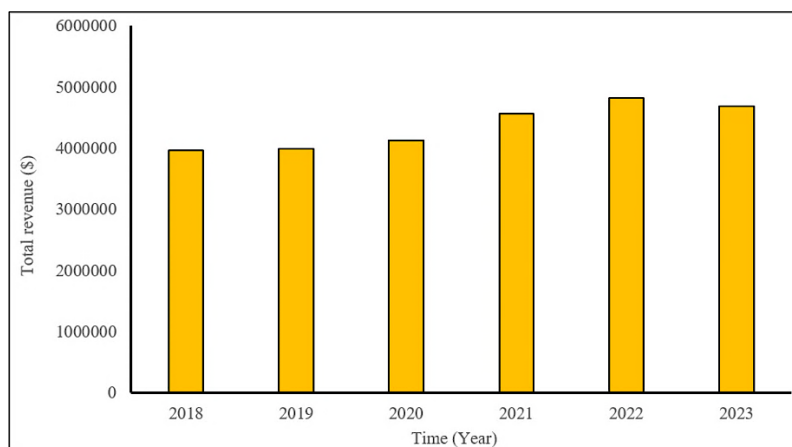


Figure 1: Chart of Total Revenue of Samsung Company

Figure 1 shows that the trend of total revenue of Samsung Electronics from 2018 to 2023. The revenue demonstrates an overall increasing pattern with a slight decrease in the final year. This indicates stable financial growth and strong operational performance during the observed period. Unit: USD.

Figure 1 illustrates the trend of the company's total revenue from 2018 to 2023, showing an overall upward movement despite a slight decline at the end of the period. In 2018, total revenue stood at USD 3,960,000 and increased marginally to USD 3,980,000 in 2019, indicating relatively stable growth in the early stage. In 2020, revenue rose more noticeably to USD 4,120,000, reflecting improved business performance. This growth

accelerated in 2021, when total revenue reached USD 4,560,000, representing a significant increase compared to the previous year. The company achieved its highest revenue in 2022 at USD 4,820,000, highlighting a strong and positive development trend. However, in 2023, total revenue decreased slightly to USD 4,680,000 suggesting a minor slowdown after several years of continuous growth, although the overall performance remained at a high level compared to earlier years.

Based on the conducted research and data evaluation, the group compiled the results for Samsung Electronics' Company. The outcomes are visually demonstrated in the subsequent chart.

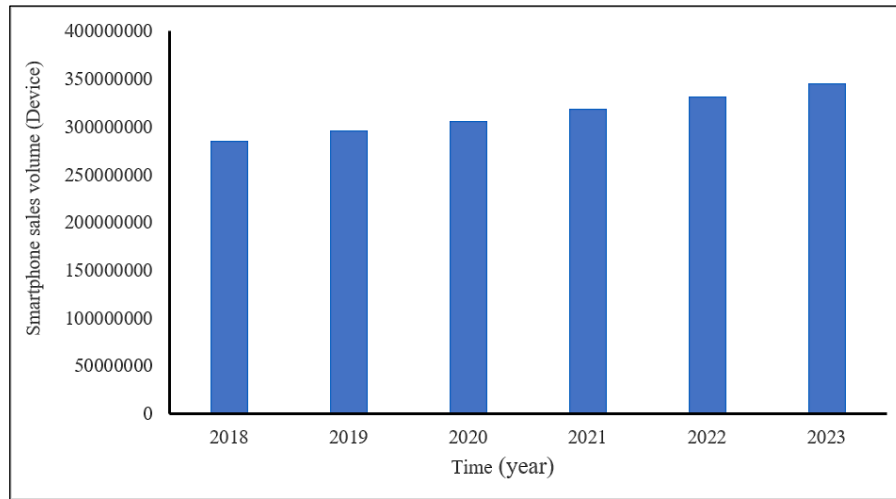


Figure 2: Chart of Smartphone Sales Volume

Figure 2 shows the smartphone sales volume over the period from 2018 to 2023. The data reveal a consistent upward trend, reflecting increasing market demand and expansion of production capacity over time.

Grey Forecast GM (1,1)

In recent years, the Grey forecasting model has achieved significant success in many studies and has been applied across various fields. Among the models, GM (1,1) is the most widely used because it provides a relatively high prediction accuracy while requiring only a small number of historical

data periods, making it applicable to a wide range of applications (15, 19, 25, 26).

The Grey method of forecasting is built on specific mathematical details and assumptions. It assumes that although system data may appear chaotic, the underlying behavior possesses an inherent trend that can be exposed through data aggregation. The specific model used is the GM (1,1), a first-order, single-variable model. The procedure begins with the accumulated generating operation to reduce randomness, creating a new sequence $X^{(1)}$ from the raw data $X^{(0)}$.

The core forecasting equation is expressed as Equation [12]:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad [12]$$

Parameter estimation for the development coefficient a and driving force b using the ordinary least squares method is given by Equation [13]:

$$\hat{a} = [a, b]^T = (B^T B)^{-1} B^T Y \quad [13]$$

Total value of the Grey GM (1,1) model is expressed as Equation [14] (13):

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a}, k = 1, 2, 3, \dots, n, n+1, 1 \quad [14]$$

In there:

$x^{(0)}(k)$: is the actual value at the time k

$\hat{x}^{(0)}(k)$: is the forecast value at the time k

To show the reliability of the proposed methodology in prediction, the model is strictly validated using established forecasting performance measures: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE)

and Mean Absolute Error (MAE). These criteria ensure that the model is robust against both average deviation and large statistical outliers.

In this study, the MAPE is employed to assess the predictive accuracy of the grey forecasting model.

The MAPE value is calculated as expressed in Equation [15] (20):

$$MAPE = \frac{1}{n} \sum_{k=2}^n \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \times 100\% \quad [15]$$

Integrated Workflow: DEA and Grey Theory

Further explanation is provided for the proposed integration between DEA and Grey Theory. The manuscript links efficiency evaluation, forecasting and maintenance decision-making through a detailed, four-step workflow:

Step 1 - Historical efficiency evaluation: Current and past operational data are processed through the Super-SBM model to calculate baseline efficiency scores.

Step 2 - Variable forecasting: The historical inputs and outputs are individually projected into the future using the GM (1,1) equations.

Step 3 - Future efficiency projection: The forecasted values from Step 2 are fed back into the DEA model. This yields a predicted future efficiency score for upcoming periods.

Step 4 - Proactive maintenance decision making: If the projected efficiency drops below a critical threshold, it signals impending equipment degradation. Maintenance managers utilize this specific foresight to proactively deploy autonomous maintenance resources to the identified bottlenecks before the degradation occurs.

Results and Discussion

Research Obtained from the DEA

Analysis

The effectiveness assessment conducted through the DEA method resulted in two notable findings, presented in Table 1.

Based on the correlation matrix presented in the table, the relationships among input and output variables under the DEA framework can be clearly observed. The results indicate that most correlation coefficients are relatively high, suggesting strong linear associations between the selected inputs of labor, materials and electricity consumption and outputs of estimated revenue and standard. Notably, labor exhibits a strong correlation with standard output of 0.72293, while estimated revenue is also highly correlated with standard output of 0.71683. In addition, electricity consumption shows moderate to strong correlations with both estimated revenue of 0.45679 and standard output of 0.59036. These findings confirm that the selected input and output variables are closely related and satisfy the underlying assumptions of DEA, thereby justifying the appropriateness of the variable selection in this study. This aligns with previous studies emphasizing the critical need for isotonicity in DEA variable selection to ensure valid efficiency benchmarking (21).

Table 1: Samsung Electronics' Ambient Efficiency

	Labor	Input Materials	Electricity Consumption	Estimated Revenue	Standard Output	Total Cost
Labor	1	0.11848	0.41293	0.44542	0.72293	0.11910
Input Materials	0.11848	1	0.51166	0.30135	0.35201	1
Electricity Consumption	0.41293	0.51166	1	0.45679	0.59036	0.51226
Estimated Revenue	0.44542	0.30135	0.45679	1	0.71683	0.30167
Standard Output	0.72293	0.35201	0.59036	0.71683	1	0.35248
Total cost	0.11910	1	0.51226	0.30167	0.35248	1

Table 2: Combined Efficiency of Samsung Electronics

DMU	Score	Rank
2005	0.1475	15
2006	0.1905	20

2007	0.1241	4
2008	0.0777	1
2009	0.1119	3
2010	0.1373	11
2011	0.1634	18
2012	0.0946	2
2013	0.1611	17
2014	0.1652	19
2015	0.1440	13
2016	0.1304	6
2017	0.1340	7
2018	0.1517	16
2019	0.1386	12
2020	0.1357	10
2021	0.1344	8
2022	0.1299	5
2023	0.1356	9
2024	0.1457	14

The efficiency of the production system was evaluated using the DEA model for 20 DMUs corresponding to the period from 2005 to 2024. The results of the efficiency scores and rankings are presented in Table 2.

Overall, the efficiency scores vary within a relatively narrow range, indicating moderate but

unstable performance across the observed period. None of the DMUs achieved full efficiency with efficiency score = 1, suggesting that there is still room for improvement in resource utilization throughout the production system.

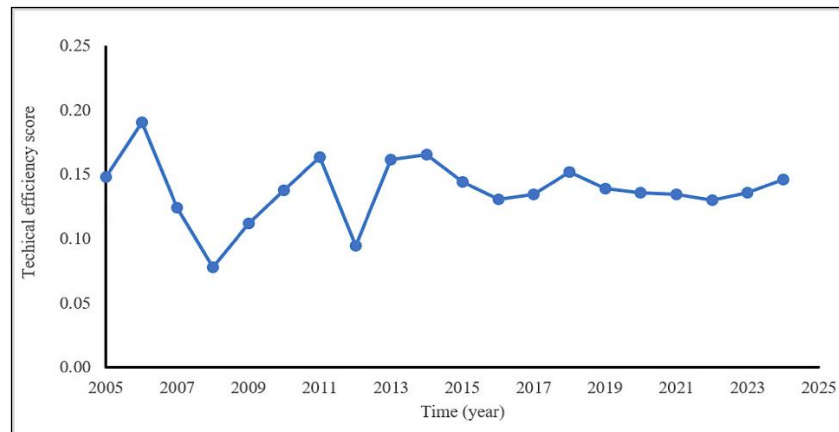


Figure 3: Efficiency Evaluation Score

The results show that the highest efficiency score is observed in 2006, while the lowest efficiency occurs in 2008 as shown in Figure 3. This significant fluctuation indicates that the production system experienced instability during the early years. After 2009, the efficiency scores gradually improved and became more stable, although minor variations still exist.

In addition, the correlation analysis between input and output variables reveals strong relationships, particularly between labor and standard output, as well as between estimated revenue and standard

output. These results confirm that the selected variables are appropriate for DEA analysis and reflect the operational characteristics of the production system.

From a managerial perspective, the DEA results indicate that inefficiencies are mainly caused by suboptimal allocation of resources such as labor and energy consumption. Therefore, improving resource management and optimizing production processes are essential to enhance system performance.

The DEA results also provide benchmark references for inefficient DMUs. By comparing inefficient units with efficient peers, it is possible to identify target values for input reduction or output improvement. This information is particularly useful for supporting decision-making in production planning and maintenance optimization. Such benchmarking capabilities are consistent with previous findings (22, 23) and recent applications of hybrid DEA models (24), which highlight how slack-based measures offer actionable pathways for operational optimization by identifying precise areas of input waste.

The efficiency results obtained from the DEA model are further used as a basis for forecasting analysis in the Grey model, as presented in the following section.

Grey Method Results

The Grey forecasting model GM (1,1) was applied to predict the future values of key production indicators in the mobile phone manufacturing system. The forecasting results, along with the actual data, are presented in Figure 4.

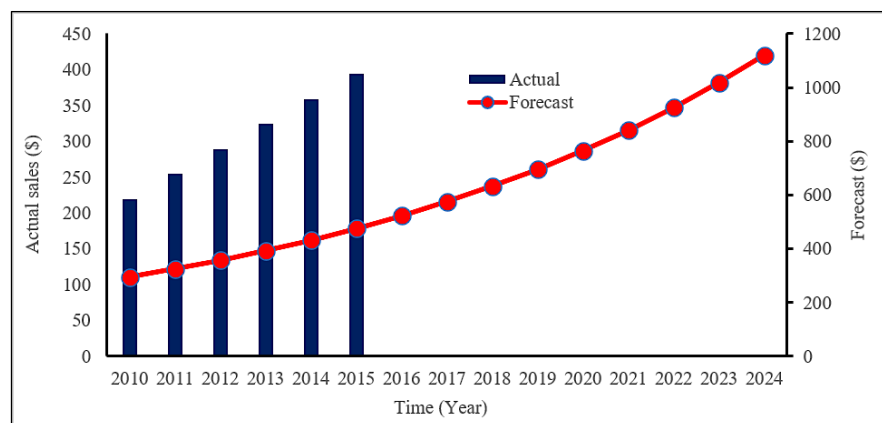


Figure 4: Forecast - to - Actual Sales Comparison

Overall, the forecasted values closely follow the trajectory of the actual data, demonstrating that the GM (1,1) model effectively captures the underlying development trend of the system. Both series exhibit a consistent upward pattern, reflecting the expansion of production capacity and the improvement of operational performance over time.

Comparison Between Actual and Forecast Values

A detailed comparison shows that the differences between actual and predicted values remain relatively small across most periods. The forecast curve generally aligns well with the actual data, particularly in the middle and later stages of the observed period.

However, slight deviations can be observed in certain years, especially during periods of rapid change. These discrepancies may be attributed to unexpected variations in production conditions, such as fluctuations in demand, operational adjustments, or external economic factors.

Despite these minor differences, the overall consistency between actual and forecast values

confirms the reliability of the Grey model in representing the system behavior.

Forecasting Accuracy Evaluation

To quantitatively assess the accuracy of the forecasting model, the MAPE was calculated. The result indicates that:

The MAPE value obtained in this study is approximately of 11.2%, indicating that the model provides acceptable prediction accuracy.

According to commonly accepted criteria, a MAPE value between 10% and 20% is considered to represent good forecasting performance. Therefore, the GM (1,1) model can be regarded as suitable for short-term prediction in this context. This level of accuracy strongly corroborates the results of prior studies applying grey system theory in industrial and economic forecasting, which consistently demonstrate the model's reliability and precision even with highly restricted historical datasets (10, 25, 26).

Trend and Pattern Analysis

The forecasting results reveal a stable and continuous growth trend in the production indicators. This suggests that the manufacturing

system is expected to maintain its upward trajectory in the near future.

The smoothing effect of the accumulated generating operation allows the Grey model to filter out random fluctuations and highlight the long-term trend. As a result, the predicted values exhibit a more regular pattern compared to the actual data.

This characteristic is particularly useful for decision-making, as it provides a clearer view of the system's development direction.

Integration with DEA Results

The forecasted values generated by the Grey model are subsequently used as inputs for the DEA model to evaluate future efficiency levels of the production system.

This integration enables a comprehensive analysis that combines:

- (a) Efficiency evaluation (DEA) for current performance
- (b) Forecasting (Grey model) for future performance

By applying DEA to forecasted data, it becomes possible to estimate how efficiently the system is expected to operate in the future. This approach allows managers to identify potential inefficiencies in advance and take corrective actions before performance deteriorates.

Managerial Implications

From a managerial perspective, the forecasting results provide valuable insights for planning and decision-making.

Specifically, the Grey model can support:

- (a) **Production planning:** estimating future output levels
- (b) **Resource allocation:** adjusting labor, materials and energy usage
- (c) **Maintenance scheduling:** anticipating equipment workload and planning autonomous maintenance activities

By integrating forecasting with efficiency analysis, the proposed framework contributes to improving operational stability and reducing unexpected downtime in the production system.

Total Productive Maintenance and Autonomous Maintenance Implementation

To transform the predictive insights from the DEA-Grey model into actionable shop-floor practices, more operational details on the implementation of

TPM and AM are required. In this framework, AM implementation delegates specific, routine maintenance activities directly to machine operators. These delegated tasks include daily initial cleaning which serves as inspection, lubrication, tightening of loose bolts and basic adjustments to calibration settings. Employee responsibilities are redefined: operators take ownership of baseline machine health, while highly skilled maintenance technicians focus exclusively on deep diagnostics and major overhauls. Operators are trained extensively using Single-Point Lessons and visual management boards to ensure standard execution.

To sustain continuous improvement, specific performance indicators are closely monitored, notably overall equipment effectiveness (OEE), mean time between failures and mean time to repair. This emphasis on operator-led AM and OEE monitoring resonates with foundational TPM literature (12, 13), which asserts that empowering the shop-floor workforce significantly reduces minor stoppages and enhances overall equipment reliability (11, 14). The mechanisms used to sustain continuous improvement include daily cross-functional Kaizen continuous improvement meetings, where operators and engineers jointly review the OEE deviations and the DEA efficiency forecasts to adjust AM checklists dynamically.

Comparative Analysis with Other Maintenance Optimization Approaches

The practical benefits of the proposed integrated framework become starkly evident when compared with traditional TPM practices and other maintenance optimization methods.

- (a) **Compared to Traditional TPM:** Traditional TPM typically relies on static, time-based inspection schedules. This often leads to over-maintenance of healthy machines and under-maintenance of stressed ones. The proposed DEA-Grey framework is dynamic, allocating maintenance based on mathematical efficiency degradation rather than the calendar.
- (b) **Compared to reliability centered maintenance and condition-based maintenance:** RCM is highly complex and focuses heavily on failure consequences, often requiring massive administrative overhead. CBM is highly effective but requires expensive physical sensors vibration, thermal installed on every machine. The proposed DEA-Grey framework

acts as a "virtual sensor"—it predicts degradation using existing production data like electricity and output, bypassing the high capital expenditure of CBM hardware. This addresses a major barrier highlighted in recent reviews of predictive maintenance, where the prohibitive cost of physical sensor networks often deters widespread adoption in modern factories (2, 8).

- (c) **Compared to predictive maintenance and machine learning (ML) models:** While ML-based represents the cutting edge, it requires vast lakes of high-quality big data to train neural networks effectively. In contrast, the Grey GM (1,1) model specifically excels with small data requiring as few as 4 data points. Therefore, the DEA-Grey framework is far more accessible, faster to deploy and highly reliable for factories that do not yet have mature big data infrastructures, making it a superior practical optimization approach for many modern manufacturing environments. While recent literature heavily favors machine learning for maintenance optimization (3, 27-29), these studies frequently acknowledge the big data bottleneck.

The proposed framework circumvents this limitation, offering a highly effective alternative to complex, data-heavy AI models (7, 30).

Conclusion

After conducting, implementing and finalizing the research project titled "Integrating DEA and Grey Methods for Autonomous Maintenance in Mobile Phone Production" the research team has achieved significant results in both theoretical insights and practical applicability.

First, the study enabled the team to develop a systematic understanding of how to evaluate and improve the performance of a modern mobile phone production system, particularly in the context of enterprises moving toward smart and data-driven manufacturing. By integrating DEA with the grey method, the research established a robust analytical framework capable of assessing production efficiency under conditions of limited, uncertain, or incomplete information a common characteristic of real-world manufacturing environments.

Specifically, DEA was employed to measure the relative technical efficiency of decision-making

units within the production system, allowing the identification of inefficiencies in resource utilization related to labor, materials and energy consumption. Meanwhile, the grey method was applied to analyze trends, relationships and future behavior of key operational indicators, thereby supporting short- and medium-term forecasting as well as decision-making under uncertainty. The combination of these two methods provides a complementary approach in which DEA evaluates current performance, while grey analysis enhances predictive and diagnostic capabilities.

Through empirical analysis, the study identified critical factors affecting production and maintenance performance, including equipment utilization, operational stability and the interaction between production activities and maintenance practices. The incorporation of TPM principles—particularly autonomous maintenance—into the DEA-Grey framework emphasizes the role of operators in maintaining equipment reliability and preventing failures, thereby contributing to sustained efficiency improvement rather than reactive maintenance.

The results indicate that the proposed framework has strong potential to enhance key performance indicators such as technical efficiency, overall equipment effectiveness and machine availability, while simultaneously reducing downtime and operational waste. In addition, the establishment of benchmark efficiency targets and reference sets through DEA provides practical guidance for performance improvement, whereas the Grey-based analysis supports strategic planning and future system development.

From an academic perspective, this study reinforces the relevance of combining efficiency evaluation models with grey system theory in industrial engineering research. It also contributes to the literature by linking production efficiency analysis with maintenance management within a unified analytical framework—areas that are often examined separately despite their strong interdependence in continuous manufacturing systems.

Beyond its methodological contributions, the research process offered valuable practical experience to the team, including data analysis, model development, interpretation of results and scientific reporting. These activities fostered essential skills such as analytical thinking,

problem-solving, teamwork and research communication, which are crucial for future careers in operations management, industrial engineering and digital transformation.

Overall, the project has successfully achieved its research objectives and opened several promising avenues for further study, such as integrating real-time production data into the DEA–Grey framework, extending the model to multi-objective decision-making, or incorporating artificial intelligence techniques to enhance autonomous and adaptive maintenance strategies. Although the current results are based on analytical and simulation-based analysis, they demonstrate strong feasibility and practical relevance for future implementation in real industrial environments.

Abbreviations

DEA: Data Envelopment Analysis, DMUs: Decision Making Units, GM (1,1): Grey Forecasting Model First Order One Variable, IT: Information Technology, MES: Manufacturing Execution Systems, MATLAB: Matrix Laboratory, IBM SPSS: International Business Machines Statistical Package for the Social Sciences, SBM: Slack Based Measure, TPM: Total Productive Maintenance.

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Author Contributions

Ta Thi Tra Giang: Parameter Investigation, Using Software, Methodology, Data Analysis, Visualization Conceptualization, Data Curation, Funding Acquisition, Project Administration, Resources, Validation, Writing - Review and Editing, Tran Quang Uoc: Writing - Original Draft, Visualization Conceptualization, Writing - Review and Editing, Nguyen Van Quang: Writing - Original Draft, Visualization Conceptualization, Writing - Review and Editing.

Conflict of Interest

The authors declare no competing interests.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this manuscript, the authors used AI-assisted language tools to improve English grammar, clarity and readability. The authors carefully reviewed, edited and validated all content and take full responsibility for the final version of the manuscript.

Ethics Approval

This study does not involve human participants or animals. Therefore, ethics approval is not required.

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