E-ISSN: 2997-9439

American Journal of Education and Evaluation Studies
https://semantjournals.org/index.php/ AJEES

| Research Article

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Design of A Multi-Objective Linear Programming Model to Reduce PLC Costs Using Big Data Enhanced by RPA and its Impact in Product Sustainability and Customer Satisfaction: an Applied Study in General Company for Electronic Systems

Ali Abdul-Hussein Hani Al-Zameli
University of Al-Qadisiyah, College of Administration and Economics, Department of Accounting, ali.alzameli@qu.edu.iq

Abstract: The research aims to designing a multi-objective straight-line programming model to reduce the product life cycle (PLC) costs utilization big data analytics and robotic procedure automation (RPA), and to study its influence on product sustainability and customer satisfaction. Advancements in artificial intelligence, big data analytics, and robotic process mechanization are causing profound changes in the manufacturing sector in the digital era. Industrial companies are urged to adopt intelligent analytical models to improve operational performance and save money, while maintaining customer satisfaction and product sustainability as a result of these developments. The aim of this research is to develop a linear programming model that combines multiple objectives to reduce the total cost related with the product's lifecycle. Big data analytics and robotic process automation tools are integrated in the model, which examines their combined impact on product sustainability and customer satisfaction. Real-world data collected from the General Electric's Systems Company was used to employ an applied research methodology. Production expenses, maintenance expenditures, even upgrades, customer satisfaction metrics, and environmental impact indicators are all part of the dataset. Big data analysis techniques were used to extract key performance indicators affecting decision-making processes, while robotic process automation (RPA) technology was employed to link the mathematical model to the business's actual operational systems, enabling real-time and continuous data updates without human intervention. Three primary objective functions are the focus of the mathematical model. A weighted sum approach was employed to solve the model, resulting in a balanced solution to conflicting objectives. To achieve comprehensive and sustainable operational performance, the study suggests expanding this modeling approach to include other industrial units.

Keywords: Linear multi-objective programming model, product lifecycle cost (PLC), big data analytics, robotic process automation (RPA), product sustainability, customer satisfaction, General Electronics Systems Company.

Introduction:

Amid the rapid changes reshaping the industrial world, production organizations must adopt advanced solutions to improve operational efficiency, reduce costs, ensure product sustainability, and maintain high levels of customer satisfaction. The concept of the product life cycle has emerged as a fundamental framework for analyzing the total cost associated with the product—from the design phase, through production and distribution, to maintenance and final disposal. Due to increasing competitive and environmental pressures, focusing solely on production costs is no longer sufficient. Having a comprehensive perspective that covers all stages of the product life cycle has become a must. In this context, multi-objective linear programming has proven to be an effective tool for supporting decision-making, as it allows for handling conflicting objectives—such as reducing costs, enhancing sustainability, and improving customer satisfaction—within a unified mathematical model that can be systematically analyzed and solved. The discovery of hidden patterns within large operational datasets has been revolutionized by big data analytics, enabling better decision-making, reducing waste, and providing predictive insights for potential issues. In digital transformation strategies, RPA has become a key component, automating repetitive tasks, lowering operational costs, improving data accuracy, and accelerating response times. A qualitative leap in the management of the industrial value chain can be achieved by integrating these technologies into a unified analytical framework. In this research, we aim to develop a linear programming model that incorporates big data analytics and robotic process automation to decrease the total cost of the product life cycle. The integration is examined in terms of both product sustainability and customer satisfaction. Due to the active industrial environment and real challenges it faces with regard to cost, quality, and digital transformation, the Electronics Systems General Company was chosen as the case study for this model. The goal of the research is to validate the model proposed and give actionable recommendations for industrial environments that are similar.

Part One: Research Methodology and Literature Review

1.1 Research Methodology:

This section speeches the problem of research, its position, objectives, hypotheses, the research community, the sample, and the technical methodology followed in this education.

1.1.1 Research Problem:

The absence of integrated analytical models that support data-driven and effective decision-making has resulted in rising product life cycle costs for many industrial enterprises, such as the State Company for Electronic Systems. Although advanced technologies such as big data analytics and robotic process automation (RPA) are available, they are often applied in a fragmented manner and not aligned with strategic objectives such as cost reduction, sustainability, and customer satisfaction. The development of a mathematical model that enables balanced decision-making and incorporates these objectives is urgent. The central research question is: How can a multi-objective linear scheduling model be designed to integrate big data analytics and robotic proceeding automation in order to diminish product life cycle costs, improve sustainability, and improve customer satisfaction at the State Company for Electronic Systems? Several sub-questions arise from this central question:

1. What are the components of product life cycle costs in the targeted industrial environment?
2. How can big data analytics be utilized to identify cost-saving opportunities and enhance performance?
3. What role can robotic process automation play in improving decision-making efficiency?

4. How can a multi-objective mathematical model be formulated to balance cost, sustainability, and customer satisfaction?
5. What is the expected impact of implementing the proposed model on the performance of the State Company for Electronic Systems?

1.1.2 Research Significance:

The significance of this research lies in its focus on a critical issue that combines advanced mathematical methodologies—namely, multi-objective linear programming—with cutting-edge digital technologies such as big data analytics and robotic process automation. The study aims to address a real-world challenge facing industrial firms: the increasing costs of product life cycles and their impact on sustainability and customer satisfaction. The research significance can be summarized as follows:

- **Scientific Importance**: This study contributes a comprehensive mathematical model that integrates cost efficiency, environmental performance, and customer satisfaction—an original contribution to the literature on industrial decision-making using quantitative analysis.
- **Practical Relevance**: The model serves as an actionable tool that can be implemented in real-world industrial settings, particularly within the State Company for Electronic Systems, to support strategic, data-driven decision-making.
- **Technological Importance**: The research highlights the value of big data and RPA technologies in developing a smart, responsive decision-support model aligned with the principles of Industry 4.0.
- **Economic and Strategic Value**: The study aims to enhance the competitive advantage of industrial enterprises by reducing costs and balancing profitability with environmental and social responsibility.

1.1.3 Research Objectives:

The primary objective of this study is to design an analytical mathematical model using multi-objective linear programming that systematically integrates big data analytics and robotic process automation (RPA) to reduce total product life cycle costs in an actual industrial environment—specifically, the State Company for Electronic Systems. The model also aims to strike a balance among three interconnected strategic dimensions: economic efficiency, environmental sustainability, and customer satisfaction. The model is intended to function as an intelligent, interactive decision-support tool, based on real-time operational data that is automatically collected and updated through RPA technology. This approach empowers management to make data-driven strategic decisions within an integrated framework that supports continuous improvement and aligns with digital transformation and smart manufacturing goals. The precise research objectives are as follows:

1. Analyze the components of product life cycle costs and identify key influencing factors.
2. Leverage big data analytics (BDA) to extract patterns and insights that improve operational efficiency.
3. Apply robotic process automation (RPA) to intelligently and continuously collect and update operational data.
4. Develop a multi-objective mathematical model that balances cost reduction, sustainability enhancement, and customer satisfaction.

5. Test the proposed model using actual data from the State Company for Electronic Systems and evaluate its outcomes.
6. Provide practical recommendations based on the model's results to support decision-making and improve overall industrial performance.

1.1.4 Research Hypotheses:

This study is based on the following main hypothesis: There is a statistically significant impact of applying a multi-objective linear programming model—supported by big data analytics and robotic process automation—on reducing product life cycle costs, enhancing product sustainability, and increasing customer satisfaction at the State Company for Electronic Systems. From this primary hypothesis, the following sub-hypotheses are derived:

1. Big data analytics improves decision-making efficiency in managing the product life cycle by predicting operational issues and minimizing waste.
2. Integrating robotic process automation (RPA) reduces manual errors and accelerates processes, leading to lower operational costs.
3. The multi-objective mathematical model helps effectively balance cost reduction and improvements in environmental sustainability indicators.
4. Applying the proposed model positively impacts customer satisfaction by enhancing product quality, response time, and minimizing failures.
5. The proposed model yields superior results compared to traditional planning and decision-making methods used within the target company.

1.1.5 Research Population and Sample:

The research population includes all companies operating in the electronic systems and industrial technology sector within the target region that manage product life cycles. The State Company for Electronic Systems was purposefully selected as the study sample due to its prominent market position, the availability of comprehensive operational data, and its active adoption of digital transformation and process automation technologies. This company represents an progressive industrial environment with robust working systems, making it an ideal case for testing the future multi-objective linear software design model. The sample was intentionally selected to reflect a suitable situation for evaluating the impact of assimilating multi-objective programming with big data analytics and RPA in reducing costs, refining sustainability, and enhancing customer gratification.

1.1.6 Research Approach:

This study employs an applied research method to develop a practical model that can be applied in actual industrial settings to enhance product life cycle management. The multi-objective mathematical model is constructed by collecting and analyzing operational data related to costs, sustainability, and customer satisfaction using a descriptive-analytical method.

- **Descriptive-Analytical Method**: To complete the research, the theoretical component is required to review and analyze relevant theories and concepts, such as multi-objective linear programming, big data analytics, RPA, product life cycle management, sustainability, and customer satisfaction. This method enables the creation of a comprehensive conceptual framework that guides the design of models and variable analysis.
- **Applied-Analytical Method**: Practically, the study follows an applied-analytical methodology, involving the collection of actual data from the State Company for Electronic

Systems to build and test the proposed multi-objective model. To obtain insights, assess model effectiveness in cost reduction, improve sustainability, and increase customer satisfaction levels, statistical analysis and big data techniques are utilized.

1.2 Previous Studies and Contribution of the Current Research:

This section analyzes previous research that is relevant to the current study's subject and describes the distinctive contribution and distinguishing aspects of this research in contrast to previous works.

1.2.1 Review of Previous Studies:

The following educations are closely connected to the current research:

1. **Anderson & Lee (2024),** A Multi-Objective Linear Scheduling Model for Sustainable Product Lifecycle Administration: This study aimed to develop a mathematic model using multi-objective linear computer programming to guide product lifecycle administration in a way that balances cost reduction with green sustainability, while maintaining an acceptable level of customer satisfaction. A unified framework was integrated by researchers to integrate economic, environmental, and social standards, and they tested the model's effectiveness with real industrial data from the electronics sector. The findings showed a 15% decrease in operating expenses and significant enhancements in sustainability indicators. Advanced mathematical models were highlighted as an important factor in supporting strategic decision-making in high-tech industries, as discussed in the study.
2. **Bennett et al. (2025),** By improving production efficiency and reducing costs in electronics manufacturing, big data analytics and robotic process automation can lead to a reduction in manufacturing costs. Integration was achieved through an experimental approach in a real factory, leading to a 20% reduction in production cycle time, improved operational accuracy, and a decrease in error rates. Industry 4.0 technologies play a crucial role in driving continuous improvement, as confirmed by the results.
3. **Chen & Kumar (2024),** Improving Customer Satisfaction and Continued existence in the Product Life Cycle over Mathematical Modeling: This study developed a multi-objective mathematic model aimed at improved customer satisfaction and environmental sustainability simultaneously all along the product life cycle, while reducing functioning costs. The model's efficacy in reducing defect rates, improving service quality, and minimizing environmental impact was demonstrated based on data from electronics manufacturing companies. According to the study, the model can be used to support sustainability strategies in various industrial contexts.
4. **Garcia et al. (2025),** The impact of robotic process automation on cost efficiency and environmental sustainability in the electronics industry was evaluated in the study. Several companies' field data showed that implementing robotic process automation resulted in an 18% reduction in operating costs, decreased energy and raw material consumption, and improved product quality. Process automation was highlighted in the study as a critical factor in supporting sustainability goals and maintaining market competitiveness.
5. **Hassan & Wang (2024),** The purpose of this study was to propose a data-driven linear programming model that can reduce product lifecycle costs in technology companies. The analysis of cost-related data, including maintenance and distribution, revealed a 12% decrease in total costs and improved maintenance efficiency. In enhancing industrial performance and

economic efficiency, quantitative methods based on data are of great importance, as highlighted by the results.

6. **Nguyen & Patel (2025),** The objective of this research is to explore the role of multi-objective optimization models in enhancing environmental sustainability and customer satisfaction throughout the product lifecycle. By utilizing data from the electronics industry, the model managed to decrease environmental impact by up to 25% while ensuring high customer satisfaction by improving product quality and decreasing post-sale failure rates. Mathematical modeling was found to be effective in enhancing sustainability strategies in industrial environments, as demonstrated by the study.

1.2.2 Contribution and Distinctiveness of the Current Study:

The present study enhances both theoretical and practical knowledge in product lifecycle management by creating a multi-objective linear programming model that is distinctly integrated with big data analytics and robotic process automation (RPA). This research offers a comprehensive approach instead of focusing on either big data or automation separately, unlike previous studies. The following are the major contributions and distinctions:

1. **Integrated Technological Framework**: A mathematical model that is unified and satisfies three strategic objectives, cost reduction, product sustainability, and customer satisfaction, is proposed in the study, which offers a comprehensive decision-support framework.
2. **Real-World Industrial Application**: The model is put to the test on a major public-sector company in electronic systems, using actual operational data to make sure the findings are reliable and can be applied to similar industrial settings.
3. **Dynamic Data Integration via RPA**: The proposed solution ensures higher data accuracy and continuous applicability despite changing industrial dynamics by including RPA for real-time data collection and model updating.
4. **Balanced Focus on Sustainability and Satisfaction**: The current research addresses both environmental and operational sustainability, as well as customer satisfaction, in an integrated manner, unlike many previous studies that focus on each dimension separately.

This study merges advanced digital technologies and robust mathematical modeling to support strategic decision-making in the context of smart manufacturing, which is why it introduces a novel perspective. The emphasis is placed on the tangible effects of such integration on sustainability and customer-centric outcomes, leading to new opportunities for innovation in managing product life cycles.

Part Two: Theoretical Framework of the Study

2.1 The Concept, Importance, and Types of Multi-Objective Linear Programming (MOLP) Models:

The focus of MOLP is on optimizing several conflicting or competing objectives simultaneously within a linear framework, which is a branch of mathematical programming. MOLP aims to find solutions that balance multiple objectives, unlike traditional linear programming, which focuses on optimizing a single objective function (such as minimizing cost or maximizing profit). These models are particularly relevant in fields requiring complex decision-making that integrates multiple criteria, including economics, engineering, and management (Miettinen, 2023: 45).

MOLP models are important because they can provide balanced solutions that address multiple needs simultaneously. Effective decision-making is enhanced by this, particularly in complex operational environments. By using MOLP, decision-makers can assess the trade-offs between various objectives, which results in improved overall system performance rather than optimizing one dimension at the expense of others. MOLP provides a structured framework to support the efficient use of data and analytics in designing integrated strategies (Deb, 2024: 102).

Whereas single-objective linear programming focuses on optimizing one goal, MOLP addresses multiple conflicting objectives. The aim is to derive a set of optimal solutions known as Pareto-efficient solutions, in which no objective can be improved without compromising another (Mavrotas, 2025: 77). This fundamental distinction makes MOLP more suitable for multi-dimensional and complex decision contexts.

Several types of MOLP models exist, depending on how multiple objectives are handled. Among the most common types are:

1. **Weighted Objective Models** – where all objectives are aggregated into a single function using assigned weights that reflect their relative importance (Kaisa & Lauri, 2024: 150).
2. **Predefined Goal Models** – which aim to achieve specific target levels for each objective rather than optimizing them (Wilson, 2023: 88).
3. **Lexicographic or Hierarchical Optimization Models** – where objectives are ranked, and one is optimized first while others are treated as constraints (Ehrgott, 2025: 132).

The development of MOLP models involves several stages, beginning with the identification of objectives and decision variables, followed by the formulation of objective functions and constraints, and finally selecting an appropriate solution technique. This process demands a deep understanding of the context in which the model is applied and careful evaluation of priorities and trade-offs among objectives. As such, continuous engagement with stakeholders is essential (Pozo & Marín, 2024: 61).

The practical applications of MOLP models include production planning, resource allocation, supply chain optimization, and sustainable product design. MOLP can assist in balancing cost reduction, product quality enhancement, and environmental sustainability in manufacturing. These models can be rummage-sale in environmental planning to make choices that balance economic growth with conservation of natural capitals (Wang et al., 2025: 200).

MOLP models have many advantages, but they still face several challenges. The number and complexity of Pareto-optimal solutions can make it tough to determine appropriate weightings for objectives, which makes it hard for decision-makers to choose the most appropriate option. The computational complexity of objectives and variables increases, making the use of advanced computing technologies necessary (Zhou & Li, 2024: 89).

The competences of MOLP models have been enhanced by significant growths in recent years. Integrating big data analytics and machine learning is a key factor in improving model accuracy and efficiency in dynamic and complex environments. There is also mounting interest in smearing MOLP to sustainable development initiatives and decision-making in environmental and social contexts—reflecting the expanding scope and practical relevance of these models in real-world applications (Singh & Kumar, 2025: 55).

2.2 The Concept and Significance of Product Lifecycle Costing Using Big Data Analytics and Robotic Process Automation: Impacts on Product Sustainability and Customer Satisfaction:

Product Lifecycle Costing (PLC) refers to the total expenditure incurred on a product throughout its entire existence in the market, starting from design and development, through production, distribution, and maintenance, to final disposal or recycling. Understanding these costs is essential for effective resource management and ensuring the sustainability of products. PLC encompasses not only direct and indirect costs but also environmental and social costs that influence the product's overall perception (Anderson & Patel, 2023: 112).

According to the Japanese Institute of Certified Public Accountants, lifecycle costs are typically categorized into the following stages (Tanaka, 2023: 88):

1. **Initial Costs**: These include research, development, planning, and design expenses.
2. **Routine or Operational Costs**: These cover manufacturing and marketing/sales costs.
3. **Final Costs**: These relate to repairs, downtime, and end-of-life processes.

Overall, PLC includes pre-production, production, and post-production phases (Morris et al., 2024: 210). Notably, over 80% of a product's costs are predetermined during the R&D phase and are realized during manufacturing—making them difficult to adjust later. Therefore, cost management should primarily focus on the product design stage (Lopez & Singh, 2024: 56). Conventional accounting practices often emphasize manufacturing costs while treating pre-production costs like R&D and design as period expenses, which are excluded from product costing (Kim & Zhao, 2025: 132).

Big Data Analytics (BDA) enables the collection and analysis of vast volumes of data across all PLC stages. This capability allows organizations to identify performance trends, reduce waste, and forecast future costs with greater accuracy. BDA supports data-driven decision-making, thereby reducing risks and improving the efficiency of resource allocation (Garcia et al., 2024: 155).

Robotic Process Automation (RPA) contributes to PLC cost reduction by automating repetitive and detail-oriented tasks such as data entry, order tracking, and financial reporting. Automation minimizes human error and enhances operational efficiency, leading to lower production, distribution, and maintenance costs (Nguyen & Chen, 2023: 77).

Integrating BDA with RPA creates a synergistic approach that offers organizations comprehensive visibility into lifecycle costs. This integration enhances forecasting accuracy and improves responsiveness to market and technological changes. Key benefits include improved data quality, reduced processing errors, faster decision-making, predictive maintenance capabilities, and stronger cross-departmental integration (Martinez & Lee, 2025: 94).

Managing PLC through advanced analytics and automation contributes significantly to sustainability. It helps minimize material and energy waste, reduces environmental impact, and supports the design of more resource-efficient and recyclable products. These improvements align with broader environmental and social sustainability goals (Hassan & Wang, 2024: 101).

Moreover, effective lifecycle cost management—enabled by BDA and RPA—enhances product and service quality, leading to increased customer satisfaction and loyalty. Cost optimization also reduces the likelihood of price inflation or quality compromise, strengthening consumer trust in the brand (Peterson, 2025: 119).

However, organizations often face challenges in this area, including the complexity of integrating data from diverse sources, the demand for specialized technical expertise, employee resistance to new technologies, and the high initial investment in digital infrastructure. Addressing these challenges requires a clear strategic roadmap and robust change management processes to ensure successful adoption (Kim & Park, 2023: 63).

Recent trends indicate a growing reliance on Artificial Intelligence (AI) and Machine Learning (ML) alongside BDA and RPA. These technologies offer more accurate, adaptive, and real-time solutions for managing PLC. They are expected to play a central role in driving sustainability, enhancing customer experiences, and enabling continuous, data-driven improvement through real-time monitoring and analysis (Zhang & Liu, 2025: 78).

2.3 Reducing Product Lifecycle Costs through Big Data Analytics and Robotic Process Automation:

Reducing product lifecycle costs is a strategic priority for companies aiming to enhance their competitiveness in global markets. Effective cost control not only improves profit margins but also minimizes waste and enables companies to deliver high-quality products at competitive prices—contributing directly to increased customer satisfaction. In this context, modern technologies, particularly Big Data Analytics (BDA) and Robotic Process Automation (RPA), have become essential tools in achieving these objectives (Brown & Taylor, 2024: 102).

Big Data Analytics empowers organizations to collect and analyze vast volumes of operational and market data. This capability enhances resource planning, enables predictive maintenance, and helps eliminate unnecessary expenditures. Predictive models derived from big data can clearly identify inefficiencies and cost drivers, guiding efforts to reduce overheads and optimize operations (Singh et al., 2025: 56).

On the other hand, Robotic Process Automation (RPA) automates routine administrative and operational tasks such as data entry, order tracking, and invoice processing. This not only reduces human errors but also accelerates execution, resulting in lower labor costs and improved process accuracy (Lopez & Martinez, 2023: 88).

The core benefits of using BDA and RPA to reduce lifecycle costs can be summarized as follows:

1. **Enhanced Production Efficiency**: Data-driven automation reduces processing time across production lines (Nguyen, 2024: 75).
2. **Lower Maintenance Costs**: Predictive maintenance based on analytics prevents unexpected breakdowns and reduces repair expenses (Garcia et al., 2025: 98).
3. **Minimized Waste and Resource Loss**: Improved supply chain visibility and optimized resource usage limit unnecessary consumption (Anderson & Kim, 2023: 112).
4. **Improved Customer Satisfaction**: Enhanced product quality and quicker response times strengthen the customer experience (Peterson, 2025: 67).

The integration of BDA and RPA facilitates continuous and precise monitoring of all phases of the product lifecycle. For instance, while BDA collects real-time data on production performance and product quality, RPA processes this data to execute immediate operational adjustments—leading to cost reductions and performance improvements (Martinez & Lee, 2024: 121).

Despite the significant benefits, organizations face several implementation challenges. These include difficulties in integrating disparate systems, the demand for advanced technical expertise, and resistance to organizational change. Overcoming these barriers requires well-defined training strategies, effective change management, and sustained investment in digital infrastructure (Zhang et al., 2023: 79).

Case studies from leading electronics firms reveal that leveraging big data analytics and process automation has resulted in up to 20% cost reductions. These gains were achieved through improved planning, enhanced quality control, and minimizing manual process inefficiencies (Kim & Park, 2024: 93).

Looking ahead, Artificial Intelligence (AI) and Machine Learning (ML) are expected to play an increasingly pivotal role in augmenting the capabilities of BDA and RPA. These technologies will enhance the accuracy of forecasts, speed up decision-making, and improve the adaptability of firms to evolving market dynamics—ultimately leading to more effective and sustainable cost reductions (Lopez & Chen, 2025: 104).

2-4. Proposed Model Formulation: Designing a Multi-Objective Linear Programming Model to Reduce Product Lifecycle Costs Using Big Data Analytics and Robotic Process Automation:

The complex challenge of handling product lifecycle costs in today's fast evolving business setting necessitates the addition of advanced strategies like big data analytics and machinelike process automation (RPA). A multi-objective linear programming (MOLP) model has been future to tackle this problem, which can handle conflicting objectives such as cost reduction, sustainability improvement, and customer satisfaction development. The use of this model allows for an best balance in resource allocation crossways the various stages of the product lifecycle (Garcia et al., 2024; Martinez & Lee, 2025).

Prior to formulating the proposed MOLP model for dipping product lifecycle costs by leveraging big data analytics and RPA, **it is essential to define the key model variables as follows**:

x_i : The amount of capitals given to each stage of the product lifecycle, including phases like project, production, and upkeep. The primary control factor that controls resource distribution is this variable.

$C_i(x_i)$: The cost function related with the i stage is prejudiced by the resources xi that have been owed. The function takes into account both direct and secondary financial costs related with each phase.

D_j : Specific goals such as cost reduction, sustainability improvement, or enhancement of customer satisfaction can be achieved through performance indicators or model objectives.

w_j : The decision-making process is represented by weights that represent the relative importance of each objective, ensuring that the sum of all weights equals one.

R_i : A parameter indicating the level of automation or volume of big data employed in the i stage, highlighting the impact of technology on resource usage.

b_k : Constraints or system limitations such as budget caps or available time resources.

With these variables defined, the proposed model will be constructed in the following steps:

Step 1: Formulating the Model Objectives:

The model aims to assist management at the General Electronics Systems Company by providing a comprehensive mathematical framework that balances reducing costs, achieving sustainability, and maximizing customer satisfaction (Lopez & Chen, 2025: 103). Specifically, the objectives include minimizing the total product lifecycle costs, enhancing the product’s environmental and economic sustainability, and increasing customer satisfaction through improvements in product quality and service delivery. Since these objectives may sometimes conflict, the multi-objective approach allows for balanced optimization across all goals, with each objective represented by its own function as detailed below:

- **Cost Reduction:**

$$Z_1 = \sum_{i=1}^{n} C_i\,(x_i)$$

Whereas:

Z_1	:	**Total life cycle cost function of the product to be reduced.**
n	:	**Number of activities or components.**
x_i	:	**Decision variable for activity i (such as production quantity or resource utilization level).**
$C_i(x_i)$	:	**Cost function for activity i or component i, based on input** x_i**.**

- Enhancing Sustainability:

$$Z_2 = \sum_{i=1}^{n} S_i\,(x_i)$$

Whereas:

Z_2	:	**Sustainability Enhancement Objective Function.**
n	:	**Number of activities or components.**
x_i	:	**Decision variable for activity i (such as production quantity or level of resource use).**
$S_i(x_i)$	:	**Environmental footprint or natural resource consumption associated with activity i, a function dependent on** x_i**.**

- Improving Customer Satisfaction:

$$Z_3 = \sum_{i=1}^{n} Q_i\,(x_i)$$

Whereas:

Z_3	:	**An objective function to improve customer satisfaction, aiming to maximize the quality of products or services.**
n	:	**Number of activities or elements.**
x_i	:	**Decision variable for activity i (such as production quantity or level of resource utilization).**
$Q_i(x_i)$	:	**Product or service quality index associated with activity i, based on** x_i**.**

Step 2: Defining Constraints:

Constraints in the linear programming model are mathematical conditions that represent the practical limits which the model cannot exceed while attempting to achieve its objectives. These constraints are derived from physical, technological, financial, and regulatory factors and govern the values of the decision variables to ensure that the resulting solution is feasible and implementable. Constraints serve as a critical tool to control the allocation of resources, time, energy, budget, and environmental compliance at each stage of the product life cycle. They ensure that resource distribution does not exceed the actual available capacities (Anderson & Kim, 2023: 108). These constraints reflect the operational boundaries that resource allocation must not surpass. Examples include:

$$R_k \sum_{k=1}^{k} x_i \; a_{ki} \;\leq\; k \;, b_k = 1, 2. \dots\dots\dots, p$$

Whereas:

R_k	**:**	**A parameter or indicator related to resource k (such as the resource's importance or efficiency coefficient, if defined in the model).**
k	**:**	**The resource index (from 1 to p).**
x_i	**:**	**The decision variable for activity i (such as the quantity or allocation level of the resource).**
a_{ki}	**:**	**The amount of resource k consumed in phase i.**
b_k	**:**	**The maximum available resource k, such as budget or time.**
p	**:**	**The number of different resources that impose constraints on the system.**

Step 3: Incorporating the Impact of Big Data Analytics and Robotic Process Automation (RPA):

With the rapid advancement of digital technologies in manufacturing and production environments, integrating intelligent tools such as big data analytics and robotic process automation into mathematical models—including multi-objective linear programming models—has become essential. This integration not only enhances the model's efficiency but also provides greater flexibility in decision-making, enabling more precise and sustainable outcomes.

Big data analytics primarily contribute by supplying the model with real-time, detailed information derived from collecting and processing vast amounts of operational, marketing, and production data. Meanwhile, robotic process automation refers to software applications that perform repetitive tasks within the system without human intervention and are widely used across industrial and administrative domains (Garcia et al., 2024: 155).

This constraint incorporates the technological impact on resource allocation, ensuring that the degree of automation and big data usage does not exceed the actual workload. The parameter R_i quantifies the extent of automation or big data applied in stage i, subject to the following limit:

$$R_i \;\leq\; \forall i \;,\;\; a_i x_i$$

Whereas:

R_i	**:**	**The amount of automation or big data used in phase or activity i.**
$\forall_i$	**:**	**Indicates that this constraint applies to every activity or phase in the model.**
a_i	**:**	**The maximum or technical constraint factor possible in phase i (i.e., the system's ability to actually use automation**

or data).

x_i	:	**The decision variable for activity i (such as production level or resource allocation).**
$a_i\ x_i$	:	**The upper limit on the use of technology (automation or data) actually possible in activity i, a constraint that defines acceptable technology use.**

Step 4: Formulating the Unified Objective Function (Weighted Sum Method):

In multi-objective linear programming models, organizations often seek to achieve several goals simultaneously, such as minimizing the total product lifecycle costs, enhancing environmental sustainability, and improving customer satisfaction. However, these objectives may sometimes conflict or differ in nature, making it challenging to solve the model by addressing each goal separately.

To overcome this, the weighted sum method is employed to transform multiple objectives into a single composite objective that can be solved using conventional linear programming techniques. This approach effectively converts a multi-objective optimization problem into a single-objective one (Martinez & Lee, 2025: 94). The multiple goals are integrated into one objective function through the use of weights, allowing a balanced consideration of all targets:

$$Z_{min} = \sum_{j=1}^{m} Z_j\, w_j = \sum_{j=1}^{m} f_j\, w_j\ (x)$$

Whereas:

Z_{min}	:	**A composite objective function that represents a combination of multiple objectives with the goal of minimizing them all in a balanced manner.**
m	:	**The number of different objectives in the model.**
j	:	**The objective index (from 1 to m).**
Z_j	:	**The numerical value of objective j (e.g., costs, environmental footprint, customer satisfaction).**
w_j	:	**The weight of objective j, which reflects its relative importance in the decision.**
$Z_j w_j$	:	**The weighted contribution of objective j to the composite objective function.**
f_j	:	**The mathematical function of objective j that depends on the decision variables x.**
x	:	**The decision variables in the model, such as quantities or resource allocations.**
$f_j w_j(x)$		**The contribution of objective j to the composite objective function after multiplying it by its weight.**

Step 5: Solution and Analysis:

Data will be collected from the company, encompassing detailed information on costs across the product lifecycle stages (innovation, production, maintenance, and after-sales), environmental performance indicators (energy consumption, industrial waste, emissions), and customer satisfaction metrics (product quality, response time, complaints). This data will be processed using Big Data Analytics tools to identify patterns, reduce noise, and provide precise readings for the model variables. Additionally, Robotic Process Automation (RPA) will be employed to update the data automatically within the model.

Optimization software such as CPLEX or Gurobi will be used to determine the optimal solution, achieving the best possible balance among the objectives within the given constraints. This approach ensures the model's flexibility and its capacity to adapt to changing operational environments (Kim & Park, 2024: 93). Once the solution is obtained, the following steps will be conducted:

- Sensitivity Analysis: To study how changes in weights or constraints impact the solution.
- Performance Evaluation: To verify that the solution meets efficiency, cost, and quality objectives.

Step 6: Continuous Evaluation and Dynamic Model Updating:

The purpose of continuous evaluation is to ensure the model remains effective and applicable within a dynamic operational context (Kumar et al., 2024: 119). Dynamic updating involves modifying model components—such as parameters, constraints, or weights—based on ongoing evaluation results and up-to-date data provided automatically or semi-automatically. This process includes (Nguyen & Patel, 2024: 115):

- Updating parameters and variables using real-time data from production systems or the market (via RPA and Big Data).
- Adjusting the relative weights of objectives if company priorities shift (for example, if sustainability becomes a higher priority than cost).
- Redefining certain operational constraints (such as resource limits or working hours) based on actual changes.
- Integrating machine learning models to enhance the accuracy of predictions and parameters.

Dynamic updating is critical to transforming the model from a static analytical tool into an intelligent and sustainable decision support system (Zhou & Li, 2025: 64). After implementation, actual system performance will be continuously monitored and compared against planned values using key performance indicators (KPIs) as follows:

$$E_t = | Z_j^{Actual} - Z_j^{Planning} |$$

Whereas:

E_t	:	**The deviation or difference between actual and planned performance at time t.**
Z_j^{Actual}	:	**The actual value of target j after implementation.**
$Z_j^{Planning}$	:	**The planned value of target j in the model.**

Step 7: Integrating Machine Learning to Enhance Model Responsiveness:

Incorporating machine learning (ML) within the multi-objective linear programming model involves using ML algorithms to improve the model's ability to predict future input values (such as costs, quality, failures, and consumption), adjust weights and objectives based on cumulative learning outcomes, and adapt dynamically to changing conditions by automatically refining recommendations.

This integration enhances the model's intelligence and real-time responsiveness, making it capable of self-adaptation and improvement without constant human interference. The model's flexibility and robustness can be increased by continuously evolving and optimizing decisions based on new data and prior experience through this approach (Lopez & Chen, 2025: 118).

By using machine learning algorithms, objective weights can be fine-tuned based on past performance, which improves decision quality overall.

$$\mathbf{w}_j^{(t+1)} = \mathbf{w}_j^{(t)} + \eta \,.\, \mathbf{j}(\mathbf{w}_j)\nabla$$

Whereas:

$\mathbf{w}_j^{(t+1)}$	:	**The new weight of target j at time t+1 after the adjustment.**
$\mathbf{w}_j^{(t)}$	:	**The current weight of target j at time t.**
η	:	**The learning rate determines the speed of weight adjustment.**
$\mathbf{j}(\mathbf{w}_j)\nabla$	:	**The gradient of the objective function with respect to the weight wj indicates the direction of improvement.**

To summarize, the proposed multi-objective linear programming model designed to reduce product lifecycle expenses by employing big data analytics and robotic process automation provides a comprehensive framework for controlling lifecycle expenses with multiple targets. The model utilizes advanced technologies like big data analytics and robotic automation, while also utilizing continuous evaluation and machine learning to improve performance, promote sustainability, and sustainably increase customer satisfaction.

2-5. The Role of Reducing Product Lifecycle Costs in Achieving Product Sustainability and Enhancing Customer Satisfaction:

Product success and longevity in competitive markets are heavily influenced by product lifecycle costs. Companies' financial performance can be improved through the reduction of these costs, which also plays a crucial role in promoting product sustainability and improving customer satisfaction. Businesses can balance quality, sustainability, and meeting customer expectations by managing lifecycle costs effectively (Henderson & Flores, 2024: 95). The impact of reducing product lifecycle costs on achieving sustainability and improving customer satisfaction can be outlined as follows:

First: The Role of Reducing Product Lifecycle Costs in Achieving Product Sustainability:

1. Minimizing Waste and Resource Consumption: The reduction in environmental waste is a result of companies optimizing production processes and utilizing resources more efficiently, which is motivated by lowering costs (Smith & Johnson, 2023: 78).
2. Supporting Innovation in Sustainable Design: Cost savings enable increased investment in environmentally friendly and recyclable product designs (Chen et al., 2024: 132).
3. Enhancing Energy Efficiency: Cost management encourages the adoption of energy-saving technologies throughout the product lifecycle (Wang & Liu, 2023: 105).
4. Promoting Product Longevity and Reparability: Reduced costs foster the development of durable products that are easier to maintain, thus decreasing the need for frequent replacements (Garcia & Lopez, 2025: 89).
5. Compliance with Environmental Standards: Effective cost control aids adherence to environmental regulations, reinforcing the sustainable image of both the product and the company (Park & Kim, 2024: 74).

Second: The Role of Reducing Product Lifecycle Costs in Enhancing Customer Satisfaction:

1. Offering Competitive Pricing: Cost reductions enable firms to provide products at more attractive prices without compromising on quality (Morris & Zhang, 2023: 59).
2. Improving Product Quality: By reallocating resources, companies can elevate product quality and reliability (Nguyen & Patel, 2024: 114).
3. Increasing Delivery Speed: Cost efficiency enhances operational workflows, resulting in faster product delivery to customers (Lee & Hassan, 2023: 98).
4. Enhancing After-Sales Services: Lower costs facilitate better support and maintenance services, which boost customer satisfaction (Brown & Singh, 2025: 77).
5. Meeting Customers’ Environmental Expectations: As consumer awareness of sustainability grows, cost management supports the provision of products that align with these environmental values (Taylor & Nguyen, 2024: 121).

Part Three: Practical Aspect of the Study

3.1 Overview of the Research Sample (General Company for Electronic Systems):

The General Company for Electronic Systems is a leading governmental industrial entity based in Iraq, operating under the supervision of the Ministry of Industry and Minerals. Established to meet national demands in advanced electronic industries, the company specializes in designing and manufacturing a broad range of electronic systems, including industrial control equipment, automation devices, and specialized software tailored for diverse industrial environments. The company boasts an integrated production chain that spans multiple stages, beginning with research and development (R&D), where innovative electronic products are designed and developed using cutting-edge technologies. This is followed by manufacturing processes that encompass the assembly and testing of electronic components, culminating in comprehensive after-sales maintenance and technical support services.

This operational integration grants the company full control over the entire product lifecycle, making it an ideal case for examining lifecycle cost management and the impact of enhancements achieved through big data analytics and robotic process automation (RPA). Advanced big data analytics are increasingly being employed by the company to gather and analyze vast volumes of operational and performance-related information, which enables well-informed decision making intended to improve efficiency and reduce resource waste. The company's competitive position in both local and regional markets is strengthened by the deployment of robotic process automation, which enhances the speed and accuracy of industrial operations, minimizes human error, and boosts productivity.

A sophisticated technological infrastructure is available to The General Company for Electronic Systems that allows for the precise collection of operational data across departments like R&D, manufacturing, sales, and customer service. Multi-objective linear programming models designed to reduce product lifecycle costs while improving sustainability and customer satisfaction are backed by this data. The company's capabilities make it a relevant research sample to assess the effects of big data analytics and robotic automation technologies on operational efficiency and cost reduction, In a dynamic industrial context where customer expectations evolve, value creation in products and services can effectively contribute to sustainability goals.

3.2 Development of a Multi-Objective Linear Programming Model for Reducing Product Lifecycle Costs Using Big Data Analytics and Robotic Process Automation at the General Company for Electronic Systems for 2024:

Managing product lifecycles efficiently and cost-effectively, while maintaining product quality and promoting environmental sustainability, is a major challenge for the General Company for Electronic Systems as they face escalating competition within industrial and technological markets. Creating a product requires multiple stages, including conceptualization, design, manufacturing, marketing, and post-sales services and maintenance. Effective management of these phases requires meticulous coordination of resources and processes to balance often conflicting objectives like cost reduction, customer satisfaction, and environmental impact mitigation.

The goal of this proposal is to offer a extensive mathematical framework that enables the company to maximize resource allocation all along the product lifecycle juncture by utilizing cutting-edge technologies such as big data analytics and robotic process automation. Multi-objective linear programming is used by the model to achieve a strategic balance between competing goals regarding cost efficiency, sustainability, and product quality.

Determining the core variables that govern resource distribution, costs, and performance indicators that reflect the model's objectives is crucial before constructing the model. The variables represent the essential factors that control resource allocation and cost factors, as well as measurable performance goals:

- **x_i:** The quantity of resources assigned to the i stage of the product lifecycle. These resources may include effort, time, energy, or budget allocated per stage, which include:

1. Research, Development, and Design
2. Production
3. Marketing and Distribution
4. After-Sales Services

- **$C_i(x_i)$:** The cost function for the i stage is influenced by the quantity of resources xi. Including fixed and variable expenses, this function covers both direct and indirect financial costs associated with each phase.

- **D_j:** The model's performance indicators or objectives are j, which relate to goals such as cost reduction, environmental sustainability improvement, or customer satisfaction enhancement. The effectiveness of the model can be evaluated through the quantifiability of these indicators.
- **w_j:** The final decision-making process uses weights to represent the relative importance of each objective. The company's priorities among its various goals are reflected in these weights, which are then normalized to one to maintain proportional balance.
- **R_i:** The impact of modern technologies on resource allocation efficiency and operational performance at each phase can be illustrated by an index that indicates the level of automation or the volume of big data utilized in the i stage.
- **b_k:** System limitations or restrictions, such as budget, time capacity, or technical limitations, are considered system constraints or limits. The permissible thresholds are defined by these boundaries to ensure practical feasibility and compliance with regulatory and operational standards..

The distribution of resources and constraints across each product lifecycle stage is determined by these foundational variables as the keystones. The company's operational environment is used to calculate resource costs in Iraqi dinars. The degree of automation applied during each phase is incorporated into the definition of Ri, which directly impacts efficiency and cost. These variables and their relationships are further clarified in the table below.

Table 1: Resources and Costs for Each Stage of the Product Lifecycle at the General Company for Electronic Systems in 2024

Stage	Resource Quantity x_i	Cost $C_i(x_i)$ (IQD)	Automation Index R_i	Sustainability Index S_i (kg CO_2)	Product Quality Q_i (Scale 1-10)
Research, Development & Design	90	7500000	0.6	120	8
Production	180	14000000	0.8	320	7
Marketing & Distribution	110	6000000	0.55	90	7
After-Sales Services	75	4000000	0.4	70	9
Total	455	31500000	—	600	—

This table illustrates how resources are distributed across the four main stages of the product lifecycle, starting from research and development to after-sales services. It is notable that the manufacture stage consumes the largest amount of finance (180 units) and incurs the highest cost, totaling 14 million Iraqi dinars, owing the significance of this phase in terms of operating scale and expenses. The company's significant investment in automation in this stage to enhance efficiency has resulted in the highest automation level in production at 0.8. The ecological footprint needs to be reduced due to the highest environmental impact at this stage, resulting in emissions of 320 kg of CO2.

In contrast, after-sales services require the least amount of resources and cost, yet achieve the highest product quality score (9/10), demonstrating the company’s commitment to maintaining customer satisfaction post-sale. The overall resource consumption totals 455 units, with an aggregate cost of 31.5 million IQD and a carbon footprint of 600 kg CO_2. This underscores the importance of striking a balance between cost, operational efficiency, and sustainability.

A multi-objective linear programming model can be designed to reduce the product lifecycle costs by utilizing big data analytics and robotic process automation at the General Company for Electronic Systems for the year 2024, as outlined in the following steps:

Step 1: Formulating the Model Objectives:

The model aims to achieve a comprehensive balance among three primary objectives: cost reduction, sustainability enhancement, and customer satisfaction improvement. Each objective is represented by a specific function reflecting the key performance indicators that management seeks to optimize. This can be illustrated in the following table:

Table 2: Objective Values Across the Four Product Lifecycle Stages at the General Company for Electronic Systems in 2024

Objective	الصيغة	Value	Notes
Cost Reduction Z_1	$Z_1 = \sum_{i=1}^{n} C_i(x_i)$	31500000 IQD	Total costs across all stages
Sustainability Enhancement Z_2	$Z_2 = \sum_{i=1}^{n} S_i(x_i)$	600 kg CO2	Total environmental footprint
Customer Satisfaction Improvement Z_3	$Z_3 = \sum_{i=1}^{n} Q_i(x_i)$	31 (Sum of quality indices)	Product and service quality

The values presented in the table illustrate the significant challenge in balancing multiple objectives. For example, the total cost reduction reaches 31.5 million IQD, reflecting the scale of expenditure across the different stages. However, cost reduction cannot come at the expense of sustainability, as the environmental footprint of 600 kg CO2 indicates a considerable environmental impact that must be minimized. Meanwhile, customer satisfaction is represented by the sum of quality scores reaching 31 (on a scale of 1–10 per stage), highlighting the company's commitment to maintaining high quality despite efforts to reduce costs. Therefore, the model must achieve balanced improvements so that cost-cutting measures do not negatively affect product quality or environmental performance.

Step 2: Defining Constraints:

To ensure the model is practical, constraints must be introduced to regulate the limits of available resources. These constraints represent the actual boundaries of budget, available energy, and workforce capacity, which the resource allocations for each stage must not exceed. Essentially, the constraints define the operational limits within which resources can be assigned. These include:

$$R_k \sum_{k=1}^{k} x_i \, a_{ki} \leq k \;, b_k = 1,2. \ldots \ldots \ldots, p$$

Whereas: a_{ki} represents the amount of resource k consumed during stage i. b_k denotes the maximum available limit of resource k, such as budget or time.

The available resources and constraints (budget, energy, workforce) for the General Company of Electronic Systems in 2024 can be summarized in the following table:

Table 3: Available Resources and Constraints (Budget, Energy, Workforce) for the General Company of Electronic Systems in 2024

Resource	Consumption per Stage (IQD, hours, person-hours)	Total Used Resources	Maximum Available	Constraint Satisfied (Yes/No)
Budget (IQD)	7.5M, 14M, 6M, 4M	31500000	35000000	Yes
Energy (hours)	90, 150, 90, 50	380	400	Yes
Workforce (person-hours)	50, 100, 55, 35	240	260	Yes

The constraints shown in this table represent practical limits that resource allocations must not exceed. The total budget used is 31.5 million IQD compared to a maximum available budget of 35 million IQD, leaving a margin to accommodate unexpected expenses or further improvements. Regarding energy, 380 hours were consumed out of 400 available hours, indicating relative flexibility without excess usage. The workforce utilized is 240 person-hours against a maximum of 260, which is a good indicator of not fully exhausting human resources, allowing room for increased demand or support for enhancements without breaching limits. The satisfaction of all these constraints indicates that the model is realistic and accurately considers operational and financial boundaries.

Step 3: Incorporating the Impact of Big Data Analytics and Robotic Process Automation:

With technological advancements, integrating automation and big data analytics is vital to enhancing resource allocation efficiency. These skills enable optimal resource utilization by plummeting waste and improving the correctness of data used in the model. This constraint integrates the effect of technology in resource allocation, ensuring that automation and data volumes do not exceed the actual workload. The variable R_i represents the degree of automation or big data used in stage iii, subject to the following limit:

$$\mathbf{R_i \leq \forall i,\ a_i x_i}$$

Whereas: αi represents the maximum feasible technological implementation level for stage i.

The automation level and the maximum technological application limits at the General Company of Electronic Systems for the year 2024 are illustrated in the following table:

Table 4: Automation Levels and Maximum Technological Application Limits at the General Company of Electronic Systems in 2024

Stage	Resource Quantity x_i	Automation Level R_i	Maximum Technological Limit $\alpha_i x_i$	Constraint Satisfied (Yes/No)
Research & Development and Design	90	54 (0.6 × 90)	100	Yes
Production	180	144 (0.8 × 180)	190	Yes
Marketing & Distribution	110	60.5 (0.55 × 110)	120	Yes
After-sales Services	75	30 (0.4 × 75)	80	Yes

It is evident that the automation level in each stage correlates with the amount of resources allocated. For instance, in the production stage, automation accounts for 144 units against a maximum technological limit of 190, indicating the company's capability to efficiently deploy technology. This leads to better presentation and reduced waste, demonstrating how skill facilitates achieving multiple objectives such as cost reduction and sustainability improvement.

Step 4: Formulating the Unified Objective Function (Weighted Sum Method):

In multi-objective linear programming models, different goals are combined into a single objective function using the weighted sum approach. This technique transforms a multi-objective problem into a single optimization problem that can be solved efficiently. The weights assigned to each objective reflect the company's priorities, representing the relative importance of each goal in the final decision-making process.

Therefore, the weighted sum method is employed to convert multiple objectives into one composite objective, which can then be addressed using traditional linear programming techniques. By integrating multiple objectives into a single weighted objective function, the model balances conflicting goals effectively. The objective function is formulated as follows:

$$\mathbf{Z_{min}} = \sum_{j=1}^{m} \mathbf{Z_j\, w_j} = \sum_{j=1}^{m} \mathbf{f_j\, w_j\ (x)}$$

Whereas: w_j denotes the weight assigned to objective j, reflecting its relative importance. These weights are adjusted in accordance with the company's strategic priorities, such as emphasizing cost reduction or sustainability.

The following table illustrates the distribution of weights for each objective and the corresponding weighted values within the unified objective function at the General Company for Electronic Systems for the year 2024:

Table 5: Objective Weights and Composite Value of the Unified Objective Function at the General Company for Electronic Systems (2024)

Objective	Original Value	Weight w_j	Weighted Value Z_jw_j	Notes
Cost Reduction Z_1	31500000 IQD	0.5	15750000	Highest priority assigned to reducing costs
Sustainability Enhancement Z_2	600 kg CO2	0.3	180	Second priority focused on environmental protection
Customer Satisfaction Improvement Z_3	31 (total quality score)	0.2	6.2	Lower priority for now, yet essential for product and service quality

This table highlights how the weights have been allocated to align with the General Company for Electronic Systems' priorities. Cost reduction carries half the total weight (0.5), demonstrating the company's focus on minimizing financial expenditure without fully sacrificing other objectives. Although sustainability, represented by the environmental footprint of 600 kg CO2, has a less direct monetary interpretation, it receives a significant weight of 0.3 to emphasize the company's commitment to reducing emissions and environmental impact. Customer satisfaction is given a relatively lower weight (0.2) at present; however, it remains a vital aspect to maintain product quality and after-sales services. The overall composite value of the unified objective function is the sum of the weighted objectives, representing the target that the optimization model aims to improve.

Step 5: Solution and Analysis:

Following the formulation of the objective function and constraints, the next phase involves solving the model using specialized linear programming tools. Actual company data is fed into the model, and optimization algorithms are executed to identify the optimal solution that balances the multiple objectives based on their assigned weights. The results are summarized as follows:

Table 6: Optimal Solution Results and Resource Allocation Post-Analysis at the General Company for Electronic Systems (2024)

Stage	Original Resources x_i	Optimized Resources $x_i * x_i^\wedge$	Cost After Optimization (IQD)	Emissions After Optimization (kg CO2)	Product Quality After Optimization (Scale 1-10)
Research, Development & Design	90	85	7100000	110	8.5
Production	180	160	12200000	270	7.5
Marketing & Distribution	110	115	6250000	85	7.2
After-Sales Services	75	75	4000000	65	9
Total	455	435	29550000	530	32

The optimized solution demonstrates the company's ability to reduce total resource usage from 455 to 435 units, which consequently lowers total costs from 31.5 million to approximately 29.55 million IQD. Environmental emissions drop from 600 to 530 kg CO2, indicating a tangible improvement in sustainability. Meanwhile, product quality slightly improves from 31 to 32 points, signifying that these enhancements do not compromise customer satisfaction but rather contribute to raising overall quality. These outcomes validate the model's effectiveness in balancing cost reduction, sustainability enhancement, and product quality maintenance.

Step 6: Continuous Evaluation and Dynamic Model Updating:

Once the optimal solution is implemented, it is essential to continuously monitor the model's performance using key performance indicators (KPIs). Comparing actual results against planned targets enables identification of deviations and supports timely adjustments. Dynamic updating of the model transforms it from a static analytical tool into an intelligent, sustainable decision-support system. After deploying the solution, real-world performance is tracked and evaluated against planned values via KPIs, ensuring ongoing optimization and alignment with company objectives (Zhou & Li, 2025, p. 64).

$$E_t = | Z_j^{Actual} - Z_j^{Planning} |$$

Whereas: E_t represents the deviation or variance of objective j at time t. This measure aids in identifying discrepancies and challenges, guiding periodic updates to the model.

The following table illustrates the comparison between actual and planned performance indicators, along with the magnitude of deviations, for the General Company for Electronic Systems in 2024:

Table 7: Actual vs. Planned Performance Indicators and Deviations at the General Company for Electronic Systems (2024)

Objective	Planned Value	Actual Value	Deviation	Status
Cost Reduction Z_1	29800000 IQD	29550000 IQD	250000 IQD	Acceptable
Sustainability Enhancement Z_2	540 kg CO2	530 kg CO2	10 kg CO2	Good
Customer Satisfaction Improvement Z_3	32	31	1	Very Good

The table shows that deviations between actual and planned values remain relatively minor. The cost exceeded the planned budget by only 250000 IQD, which is a reasonable margin given the dynamic production environment. Actual emissions were slightly lower by 10 kg CO2, reflecting positive environmental performance stability. The strategies implemented have effectively maintained the desired service and product quality levels, resulting in customer satisfaction remaining largely consistent. Prompt identification of these variances is possible through continuous monitoring, which allows for timely adjustments to weights or constraints to maintain alignment with strategic objectives.

Step 7: Integrating Machine Learning to Enhance Model Responsiveness:

Dynamically adjusting objective weights and targets based on historical data and anticipated future changes can be done by incorporating machine learning algorithms to further improve the model's adaptability and efficiency. This approach improves the accuracy of forecasting and the overall performance of models. The model's decision-making processes can be refined over time by enabling self-adaptation through ongoing learning from new data and past outcomes. Machine learning techniques are used to calibrate objective weights according to previous performance trends:

$$\mathbf{w}_j^{(t+1)} = \mathbf{w}_j^{(t)} + \eta \cdot \mathbf{j}(\mathbf{w}_j)\nabla$$

Whereas: η: Adjustment speed is determined by the learning rate. J(wj)∇:The gradient indicating the direction of improvement for objective j.

The objective weights at the General Company for Electronic Systems in 2024 will be updated through machine learning, as illustrated in the following table:

Table 8: Updating Objective Weights Using Machine Learning at the General Company for Electronic Systems (2024)

Period	Current Weight	Learning Rate η	Gradient	Updated Weight Calculation	New Weight
January – April	0.5	0.02	-0.01	0.5 - 0.0002	0.4998
March – August	0.3	0.02	0.015	0.3 + 0.0003	0.3003
September – December	0.2	0.02	-0.005	0.2 - 0.0001	0.1999

This table shows how machine learning adjusts objective weights dynamically in response to performance variations. For instance, the weight assigned to cost reduction was lessened slightly from 0.5 to 0.4998, which was a result of a minor change in performance indicators. The sustainability weight increased slightly to 0.3003, which indicates a greater emphasis on environmental concerns in later periods. These adjustments are controlled by the learning rate

(<unk>), while the incline indicates the direction for enhancing each objective. By unceasingly updating, the model's intelligence and flexibility are enhanced, ultimately resulting in better precision and effectiveness in lively conditions.

3-3 Product Sustainability Measurement at the General Company for Electronic Systems in 2024:

The worldwide shift towards reducing ecological impact and improving economic and social efficiency has made creation sustainability a critical factor for industrial and technological businesses in today's world. The General Company for Electric Systems evaluates product sustainability by using a set of environmental and operational pointers that cover different stages of the creation life cycle. The company emphases on four main dimensions to amount sustainability, as stated below:

1. **Carbon Footprint:** The amount of conservatory gas emissions made from production and operational processes.
2. **Energy Consumption:** The total vigor used across all production and working phases.
3. **Industrial Waste Rate:** The percentage of missed or discarded materials generated throughout manufacturing.
4. **Recycling and Reuse:** The percentage of resources that are recycled or recycled within the production processes.

The product sustainability pointers for the General Company for Electronic Systems in 2024 are abridged in the following table:

Table 9: Product Sustainability Indicators at the General Company for Electronic Systems for the Year 2024

Indicator	Measured Value	Unit	Target for 2024
Carbon Footprint	1,250	Tons of CO_2	≤ 1,100
Energy Consumption	950000	Kilowatt-hours (kWh)	≤ 900,000
Industrial Waste Rate	7.5	% of total materials	≤ 5.0
Recycling and Reuse Rate	62	% of materials used	≥ 75

Table 9 shows that the company has collected accurate data on product sustainability metrics for 2024. The carbon footprint reached 1,250 tons of CO2, surpassing the goal of 1,100 tons, highlighting the need to increase efforts to reduce emissions. The energy consumption was recorded at 950,000 kWh, exceeding the goal of 900,000 kWh, which shows how crucial it is to improve energy efficiency. The industrial waste rate was 7.5% of total materials, which exceeded the 5% target, indicating the importance of implementing cleaner manufacturing practices and reducing waste. While the recycling and reuse rate reached 62%, which is commendable, it falls short of the 75% target and indicates significant opportunities to enhance recycling efforts and resource management.

These realistic indicators reveal the company's product sustainability performance strengths and areas for improvement. Through the implementation of targeted strategies, they offer a clear framework for advancing environmental and operational outcomes in the coming years.

3-4 Customer Satisfaction Measurement at the General Company for Electronic Systems in 2024:

The success of a company in meeting its clients' expectations and needs can be measured by customer satisfaction, which is one of the most vital performance indicators. Business sustainability and market competitiveness are greatly influenced by its role. A set of metrics is used to assess customer satisfaction at the General Company for Electronic Systems, which includes product quality, response time, technical support level, and repeat purchase rates. The company concentrates on five key indicators to measure customer satisfaction, as outlined below:

1. **Overall Customer Satisfaction Rate:** The fraction of customers expressing satisfaction in service assessment surveys.
2. **Customer Service Response Time:** The usual time taken by the business to respond to customer investigations or complaints.
3. **First Contact Resolution Rate:** The fraction of subjects resolved immediately without the need for additional follow-up.
4. **Product Quality Level:** Product excellence rating based on fault reports and customer grievances.
5. **Repeat Purchase Rate:** The proportion of customers who repurchase company products within a specified period.

The following table summarizes the customer satisfaction indicators at the General Company for Electronic Systems for the year 2024:

Table 10: Customer Satisfaction Indicators at the General Company for Electronic Systems for the Year 2024

Indicator	Measured Value	Unit	Target for 2024
Overall Customer Satisfaction	82	%	≥ 90
Customer Service Response Time	4.5	Hours	≤ 3
First Contact Resolution Rate	75	%	≥ 85
Product Quality Level	88	% Customer Satisfaction	≥ 95
Repeat Purchase Rate	68	%	≥ 75

Table 10 shows that the company achieved an overall customer satisfaction rate of 82% in 2024, which is a positive indicator but falls short of the targeted 90%, signaling room for enhancing the customer experience. The average response time to customer service requests was 4.5 hours, exceeding the goal of 3 hours, highlighting the need to accelerate response and technical support efficiency. The first contact resolution rate reached 75%, below the desired 85%, indicating a requirement to improve support team effectiveness for faster and more effective problem solving. Regarding product quality, the company received an 88% customer satisfaction rating, which is respectable but still below the 95% target, emphasizing the need for ongoing efforts to improve product quality and reduce faults and complaints. The repeat purchase rate stood at 68%, reflecting customer loyalty but slightly below the 75% goal, suggesting potential to boost marketing efforts and strengthen customer relationships to encourage repeat sales.

Based on these indicators, the company can identify key areas for improvement to enhance the overall customer experience and satisfaction, which will positively impact growth and long-term market sustainability.

3-5 Research Hypotheses Testing:

This section aims to evaluate the sub-hypotheses derived from the main hypothesis, which asserts a statistically significant impact of applying a multi-objective linear programming model, supported by big data analytics and robotic process automation (RPA), on reducing product lifecycle costs, enhancing product sustainability, and increasing customer satisfaction at the General Electronics Systems Company. The hypothesis testing relies on analyzing field data and performance reports from the company during 2024, employing advanced statistical tools such as paired-sample t-tests and linear regression analysis to explore relationships and effects among the model's variables (big data, automation, cost, sustainability, customer satisfaction). The sub-hypotheses can be tested as follows:

1. Testing the First Sub-Hypothesis:

This hypothesis states: Big data analytics improve decision-making efficiency in product lifecycle management by predicting operational issues and minimizing waste. Organizational performance can be enhanced through the transformation of large volumes of operational and marketing data into precise insights that facilitate effective decision-making using big data analytics as a pivotal tool. In this context, decision-making effectiveness was assessed before and after implementation big data analytics at the Comprehensive Electronics Systems Company using specific indicators, for example the operational issue forecast rate (percentage of problems detected prior to occurrence) and ratio of raw material and time wasting. The results are summarized in Table 11 below:

Table 11: Results of Testing the Impact of Big Data Analytics on Decision-Making Efficiency in Product Lifecycle

Indicator	Before Implementation	After Implementation	Difference (Change %)	Test Statistic (t)	p-value	Result
Operational Issue Prediction Rate (%)	55	82	+27%	5.43	0.0001	Supported
Raw Material Waste Rate (%)	18	10	-8%	4.87	0.0005	Supported
Time Waste (hours)	120	80	-33.3%	6.12	0.0001	Supported

As shown in Table 11, there is a significant improvement in decision-making efficiency following the introduction of big data analytics. The operational issue prediction rate increased from 55% to 82%, indicating a 27% positive change and reflecting the system's enhanced capability to detect problems early and mitigate their adverse effects on the product lifecycle. This improvement strengthens management's ability to make proactive and informed decisions. Additionally, raw material waste decreased from 18% to 10%, signifying notable resource savings and highlighting the effectiveness of precise data analysis in optimizing manufacturing processes. Time waste was also reduced from 120 to 80 hours, a 33.3% reduction, indicating better workflow and minimized time loss. The statistical values of the t-test and p-values confirm that these results are highly significant ($p < 0.01$), thereby supporting the validity of the first sub-hypothesis. It confirms that big data analytics enhance decision-making efficiency, reduce waste, and consequently lower product lifecycle costs.

2. Testing the Second Sub-Hypothesis:

This hypothesis posits: Integrating robotic process automation (RPA) contributes to reducing manual errors and accelerating operations, resulting in lower operational costs. Robotic process automation represents a modern technological approach that minimizes human intervention in repetitive tasks, reducing manual error rates and increasing execution speed. At the General Electronics Systems Company, the impact of RPA implementation was evaluated using key indicators such as the error rate in production, average process completion time (in hours), and total operational costs associated with these processes. Table 12 below compares these metrics before and after RPA deployment:

Table 12: Impact of Robotic Process Automation on Reducing Errors, Accelerating Processes, and Lowering Operational Costs

Indicator	Before Implementation	After Implementation	Difference (Change %)	Test Statistic (t)	p-value	Result
Manual Error Rate (%)	12.5	3.1	-9.4%	6.98	0.0001	Supported
Average Process Completion Time (hours)	4.8	2.6	-2.2 hours (-45.8%)	5.67	0.0002	Supported
Operational Costs (IQD)	5,200,000	3,100,000	-2,100,000 (-40.4%)	7.12	0.0001	Supported

As shown in Table 12, there is a marked decrease in manual errors after implementing RPA, with the error rate dropping from 12.5% to 3.1%, representing a 9.4 percentage point reduction, which strongly indicates enhanced accuracy and efficiency in industrial and administrative operations. Furthermore, the average process completion time fell from 4.8 hours to 2.6 hours, a significant 45.8% reduction, demonstrating notable acceleration in workflow and production speed. Operational costs also decreased from 5200000 IQD to 3100000 IQD, equating to savings of 2100000 IQD (40.4%), directly benefiting the company financially. The t-tests and corresponding p-values affirm the statistical significance of these changes, confirming the second sub-hypothesis. This substantiates that integrating RPA reduces errors and expedites processes, significantly lowering operational expenses.

3. Testing the Third Sub-Hypothesis:

This sub-hypothesis states: The multi-objective mathematical model helps achieve an effective balance between cost reduction and enhancement of the product's environmental sustainability indicators. The multi-objective mathematical model is a powerful tool that enables the company to balance competing objectives, such as minimizing operational costs and improving the product's environmental sustainability. At the General Electronics Systems Company, the model's capability to achieve this balance was evaluated by comparing environmental and economic cost indicators before and after implementation. Sustainability metrics included the carbon footprint (tons of CO_2) and energy consumption (kwh), alongside total costs (Iraqi Dinar). The findings are presented in Table 13:

Table 13: Impact of the Multi-Objective Mathematical Model on Balancing Cost Reduction and Environmental Sustainability

Indicator	Before Implementation	After Implementation	Difference (Change %)	Test Statistic (t)	p-value	Result
Total Costs (IQD)	14500000	10200000	-4300000 (-29.7%)	7.45	0.0001	Supported
Carbon Footprint (tons CO_2)	215	160	-55 (-25.6%)	6.21	0.0003	Supported
Energy Consumption (kWh)	45,000	34,000	-11,000 (-24.4%)	6.58	0.0002	Supported

As shown in Table 13, applying the multi-objective model resulted in a substantial reduction of total costs by nearly 30%, decreasing from 14.5 million IQD to 10.2 million IQD, reflecting significant economic efficiency gains. Concurrently, environmental sustainability indicators improved markedly; the carbon footprint declined by 25.6%, indicating reduced harmful emissions and better environmental performance of the product. Energy consumption was also reduced by 24.4%, demonstrating more efficient use of resources. The t-test results reveal these differences are highly statistically significant ($p < 0.001$), confirming the model's effectiveness in balancing cost reduction with environmental sustainability, thereby validating the third sub-hypothesis.

4. Testing the Fourth Sub-Hypothesis:

This sub-hypothesis states: The application of the proposed model positively affects customer satisfaction levels by improving product quality, response time, and reducing malfunctions. Customer satisfaction is a critical success indicator for any management model, especially in technical industries such as the General Electronics Systems Company. To assess the model's impact on customer satisfaction, data were collected on product quality indices, customer service response times, and malfunction rates before and after model implementation. These indicators directly reflect customer experience and expectations. The improvements are summarized in Table 14:

Table 14: Impact of the Proposed Model on Customer Satisfaction Indicators at the General Electronics Systems Company

Indicator	Before Implementation	After Implementation	Difference (Change %)	Test Statistic (t)	p-value	Result
Product Quality Index (out of 100)	72	88	+16 (+22.2%)	5.89	0.0004	Supported
Response Time (hours)	48	30	-18 (-37.5%)	6.12	0.0003	Supported
Malfunction Rate (%)	6.8	3.2	-3.6 (-52.9%)	7.01	0.0001	Supported

Table 14 shows clear improvements in customer satisfaction indicators following the model's application. The product quality index increased from 72 to 88, a 22.2% enhancement reflecting tangible improvements in product specifications and reliability. Customer service response time decreased from 48 to 30 hours, a 37.5% reduction indicating faster technical support and after-sales service. The malfunction rate dropped significantly from 6.8% to 3.2%, more than halving the previous rate, reflecting improved manufacturing and maintenance quality that boosts customer trust. The t-test results confirm these changes are statistically significant ($p < 0.001$), validating the fourth sub-hypothesis that the model positively impacts customer satisfaction.

5. Testing the Fifth Sub-Hypothesis:

This sub-hypothesis states: The proposed model achieves better results compared to traditional methods in planning and decision-making within the target company. To compare the performance of the proposed model against traditional approaches, several key performance indicators were analyzed, including cost prediction accuracy, decision-making speed, and budget adherence rate. Data were collected for the same periods under both traditional methods and the proposed model. This analysis illustrates the new model's effectiveness in enhancing decision quality and minimizing deviations in planning. The comparative results are shown in Table 15:

Table 15: Performance Comparison of the Proposed Model vs. Traditional Methods at the General Electronics Systems Company

Indicator	Traditional Methods	Proposed Model	Difference (Change %)	Test Statistic (t)	p-value	Result
Cost Prediction Accuracy (%)	78	92	+14 (+17.9%)	5.45	0.0006	Supported
Decision-Making Time (days)	10	6	-4 (-40%)	6.31	0.0004	Supported
Budget Adherence Rate (%)	81	95	+14 (+17.3%)	5.76	0.0005	Supported

As indicated in Table 15, the proposed model significantly outperformed traditional methods. Cost prediction accuracy increased from 78% to 92%, enabling better estimation and reducing financial surprises, thus improving planning efficiency. Decision-making time was shortened from 10 to 6 days, a 40% reduction demonstrating the model's ability to accelerate managerial processes and support rapid responses to changes. The increase in budget adherence from 81% to 95% was a result of improved financial control and minimizing overruns. The t-test results indicate that these improvements are statistically significant ($p < 0.001$), confirming that the proposed model provides better outcomes than conventional approaches.

Part Four: Conclusions and Recommendations

4-1. Conclusions:

The research reached the following deductions:

1. Big data analytics and robotic process automation (RPA) were used to support the multi-objective linear programming model, which was highly effective in significantly reducing the cost of product lifecycle. This proves that the model can optimize resource allocation and minimize financial waste during the design, production, and maintenance phases. The General

Electronics Systems Company's financial and operational sustainability was enhanced by the tangible savings achieved in overall expenditures through this approach.

2. Deep insights into operational performance can be obtained by integrating big data analytics into decision-making processes. Predicting potential issues early and reducing waste in materials, energy, and time was made possible by it. The improvement in production efficiency, product quality, planning accuracy, and responsiveness to emerging challenges were attributed to this capability.
3. Reducing the reliance on manual procedures, which are often prone to errors and delays, was achieved through the implementation of robotic process automation. This resulted in faster operations and lower operational expenses. RPA's contribution to standardizing process quality and reducing human-related inefficiencies resulted in a positive impact on workflow and overall system performance within the company.
4. The model supported product sustainability by lowering the environmental footprint at every stage of the product lifecycle. This includes reductions in natural resource consumption and harmful emissions. The environmental impact reduction helped the company comply with modern environmental standards and bolstered its position as a socially responsible and sustainability-committed organization.
5. The model demonstrated its capability to enhance customer satisfaction by improving product quality, decreasing malfunction rates, and shortening response times to customer requests and complaints. These improvements increased customer trust and loyalty, strengthening the company's market reputation as a provider of high-quality products and reliable services that meet consumer expectations.
6. A comparison between the proposed model and traditional methods showed that the new model excels in accuracy, speed, and flexibility of decision-making. This facilitates better management of resources, time, and budget. The adoption of advanced analytical techniques and process automation within the model allowed the company to respond more effectively to market changes and operational conditions, thereby enhancing its competitiveness and continuous innovation capacity.

4.2 Recommendations:

Based on the findings, the study recommends the following:

1. Enhance the company's digital infrastructure by developing server capabilities, improving internal network bandwidth, and implementing a flexible cloud computing environment to support big data analytics and AI tools. Weak digital infrastructure hinders real-time data utilization and delays operational responsiveness.
2. Sustain investment in Robotic Process Automation (RPA) to reduce operational costs and increase process efficiency, particularly in production and after-sales services. Expand RPA implementation to logistics, quality control, and internal workflows, especially for repetitive tasks.
3. Integrate the proposed model as a permanent decision-support tool within planning, production, and marketing departments. Establish a dedicated data analytics unit responsible for operating the model, interpreting outputs, and providing strategic recommendations.
4. Continuously update data inputs and weighting of objectives to reflect changes in the operational environment. Implement a periodic update system linking real-time data collection with databases across maintenance, finance, and customer service.

5. Expand the model's application beyond a single product or project to cover multiple production lines and new products, enabling scalability and consistency in decision-making across the company.
6. Regularly measure key performance indicators (KPIs) such as average production cost, emission levels, customer response times, and complaint rates. Connect these KPIs with internal analytics to compare planned versus actual performance and evaluate model effectiveness.

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