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The Fairness Analysis of the Supply Chain in the Saipa Automotive Group: Examining Deviations and Supplier Performance Using a Neural Network Approach

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Abstract

The fairness of the supply chain refers to the ways in which members of the supply chain interact or intersect with one another. Due to imperfections in competitive markets, some members may exploit their position or circumstances, allowing them to gain excessive advantages over others. Within the Saipa Automotive Group, two suppliers, Sazehgostar and Megamotor, play a crucial role in the supply chain for Saipa, Pars Khodro, Saipa Citroën, Benro, and Zamyad. The objective of this research is to examine the deviations and production stoppages, as well as the impact of supplier performance on the fairness of parts distribution within the Saipa Group companies, and to provide solutions aimed at improving supply chain performance. To achieve this, statistical analysis of production stoppage reports from the Saipa Automotive Group during the first six months of 2024 has been conducted to investigate the behavior of automotive parts suppliers within the group's manufacturers. The results of the statistical analyses indicate that the suppliers' goal is to meet weekly and monthly production targets; however, they did not exhibit consistent performance in achieving daily production plans across the automotive companies in the group. Ultimately, a decision-making framework based on neural networks is proposed to enhance supply chain performance.

Keywords: Fair supply chain, Suppliers, Statistical analysis, Neural network, Data-driven decision making.

1 | Introduction

Every economic entity has the mission of producing and providing services aimed at enhancing the effectiveness and profitability of the enterprise. Production line stoppages (For any reason) hinder the fulfillment of the missions of production firms. Saipa is an economic entity with the mission of automobile manufacturing, and many factors can obstruct the execution of this mission, which encompasses various parameters and aspects. The fairness of parts distribution in the supply chain is one such factor.

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The fairness of the supply chain refers to the ways in which members of the supply chain interact or intersect with each other. Due to imperfections in competitive markets, some members may exploit their position or circumstances, allowing them to gain excessive advantages over others. Such unfair behaviors may manifest as unfair pricing, unfair trading, or stoppages in production lines [1].

In the Saipa Automotive Group, two suppliers, Sazehgostar and Megamotor, play a key role in the supply chain for Saipa, Pars Khodro, Saipa Citroën, Benro, and Zamyad. The objective of this research is to examine the deviations and production stoppages, as well as the impact of supplier performance on the fairness of parts distribution within the Saipa Group companies, and to provide solutions for improving supply chain performance in this company.

To this end, this research consists of two phases:

In the first phase of the research, an attempt is made to investigate the behavior of automotive parts suppliers within the group's manufacturers by utilizing statistical analysis of production stoppage reports from the Saipa Automotive Group during the first six months of 2024. The question for this phase of the research is:

First phase research question

Is the distribution of parts in the companies Saipa, Pars Khodro, Saipa Citroën, Benro, Saipa Diesel, and Zamyad balanced?

In the second phase of the research, a decision-making framework based on the implementation of a neural network model is proposed to improve the performance of suppliers within the Saipa Automotive Group.

Second phase research question

What strategies can be employed to enhance supply chain performance?

2 | Literature Review

In the literature related to the fair distribution of parts by suppliers in the supply chain, various models and methods are employed to investigate this issue in two phases. The first phase focuses on examining and analyzing the relationships among supply chain members both quantitatively and qualitatively to determine whether the relationships are fair or not. The second phase involves prescribing and presenting quantitative and qualitative solutions to establish fair relationships within the supply chain.

To assess the fairness or unfairness of distribution, various ethical and social models and methods can be utilized in this context. Some common models and methods for examining the fairness of distribution include: 1) qualitative, judgmental, and ethical models, 2) economic models, and 3) statistical tests. These models and methods can assist you in evaluating the fairness of distribution, enabling more rational decision-making and leading to a deeper understanding of supply chain relationships.

Additionally, in the literature related to how to create a fair distribution of parts by suppliers in the supply chain and provide prescriptive solutions for it, various models and methods are used, including: 1) optimization models, 2) simulation models, 3) neural networks, 4) decision-making models, and 5) game theory models. *Fig 1* illustrates the categorization of models and methods for addressing fair supply chain issues.

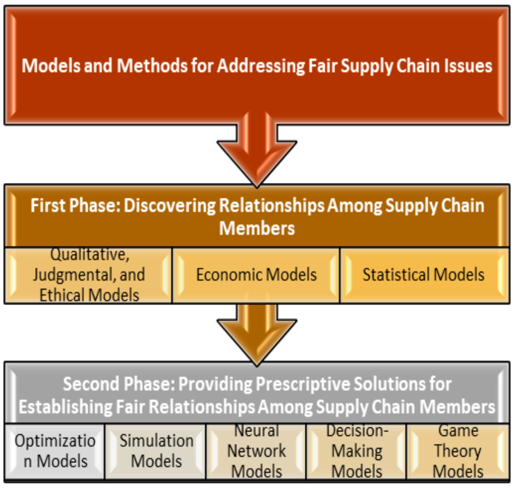

Fig 1. Classification of models and methods for addressing fair supply chain issues.

The following is a review of previous research related to fairness in supply chains.

In 2009, a study [2] explored the relationship between fairness and organizational outcomes in buyer-supplier relationships, aiming to establish a conceptual model of fairness to advance empirical research in supply chain management.

In 2013, another article [3] noted that while different disciplines focus on various aspects of supply chain management, they agree that effective coordination among independent firms is essential. The central hypothesis suggests that preferences for fairness drive these coordinations.

A 2016 study [4] examined whether standard supply chain model outcomes apply to repeated relationships, highlighting the unresolved issue of which party, manufacturer or retailer, has more power to extract profits. The findings showed that supply chain members tend to choose similar margins, leading to more equitable profit distributions than predicted by non-cooperative models.

In 2021, research [5] identified fairness as a significant issue in supply chains, influencing organizational sustainability, especially from a social perspective. This study aimed to assess the impact of fairness perspectives on multi-level supply chain relationships and analyze the dynamics of fair arrangements during relationship development.

A separate 2021 article [6] investigated the establishment of fair relationships in a green supply chain involving a manufacturer and a retailer, using a Stackelberg game model to analyze decision-making under centralized and decentralized conditions. The findings confirmed the model's validity through numerical simulations.

In recent years, the application of machine learning methods, particularly neural networks, has significantly increased in improving supply chain performance and enhancing fairness within it. Supply chains, as complex systems involving interactions among suppliers, manufacturers, distributors, and customers, require accuracy in demand forecasting and inventory management. Utilizing predictive analytics based on neural networks can help improve demand forecasting accuracy, thereby reducing inventory costs and increasing supply chain efficiency [4].

Neural networks are capable of identifying complex patterns in historical data and providing precise demand predictions using real-time data and market insights. These predictions can assist companies in effectively adjusting their supply strategies and preventing existing inequalities in the distribution of components. Furthermore, considering the uncertainties and market fluctuations, neural networks can enhance decision-making and improve supply chain agility [4].

Additionally, employing neural networks in identifying and assessing risks and challenges within the supply chain can contribute to enhancing fairness in interactions among its members. Overall, these methods can lead to a reduction in inequalities and the establishment of fairer conditions in the supply chain. Therefore, the implementation of neural networks and other machine learning techniques is regarded as an effective tool for improving supply chain performance and increasing fairness within it [4], [7], [8].

This research also utilized statistical analyses, specifically two-way Analysis of Variance (ANOVA), to examine production stoppages in companies like Saipa and others, focusing on two leading suppliers, Megamotor and Sazehgostar. Additionally, a neural network-based decision-making framework was proposed to enhance supplier performance.

3 | Problem-Solving Method

In production units, an annual production plan is established at the start of each year based on available capacity, labor hours, raw materials, market demand, and other factors. This plan is then used to create monthly and weekly schedules, detailing daily production targets.

After the weekly plan is communicated, companies begin production according to the schedule. However, actual production often deviates from the plan due to various issues, such as production line stoppages caused by poor-quality parts, material shortages, equipment failures, and inadequate operator skills. These stoppages are particularly linked to supplier performance.

In the Saipa automotive group, key suppliers like Sazehgostar and Megamotor significantly impact the supply chain for several companies. Therefore, assessing the fairness of parts distribution from these suppliers is crucial for maintaining production satisfaction.

This research has been conducted in two phases: In the first phase, the study examines production deviations and stoppages, and the effects of supplier performance on the fairness of parts distribution within the Saipa group companies. In the second phase, a decision-making framework based on neural networks is proposed to enhance the distribution performance of suppliers, resulting in increased profits for the Saipa automotive group. The problem-solving method for each phase of the research is explained in detail below.

Phase 1. Supply chain performance assessment

In *Phase 1*, a statistical analysis of production line stoppage reports in the Saipa automotive group during the first six months of the year 2024 is conducted. The aim is to examine the behavior of automotive parts suppliers within the group's automotive companies. Given the availability of data related to stoppages from Saipa, Pars Khodro, Saipa Citroën, Bonro, and Zamyad, a statistical analysis using two-way ANOVA is performed on the mentioned data.

The ANOVA test is a statistical method used to compare the means of three or more different groups. The main objective of ANOVA is to determine whether the means of the groups are different from each other. This test is based on analyzing the variance between groups and within groups.

In ANOVA, the null hypothesis states that the means of all groups are equal, while the alternative hypothesis asserts that at least one of the means is different. ANOVA calculates the F value, which indicates the ratio of variance between groups to variance within groups. The data is then evaluated using the F distribution table and the p-value[1].

In two-way ANOVA, an additional factor variable is included in the model, allowing the examination of the impact of two factor variables on the response variable. The null hypothesis in this test is that the means of the two groups are equal, while the alternative hypothesis states that the means are different.

[1] The p-value is a measure used in hypothesis testing and statistical analysis. The p-value indicates the probability that the observed results of a test or statistical analysis would occur if the null hypothesis were true. In other words, the p-value shows how compatible the observed data is with the null hypothesis.

Furthermore, the analysis compares the average production loss ratios attributed to the two companies, Megamotor and Sazehgostar, for the Saipa automotive group across three time frames: Daily, weekly, and monthly, during the initial six-month period of the year 2024, using the two-way ANOVA test.

Phase 2. Improving supply chain performance

In this section, an effort is made to provide a solution for improving supply chain performance based on the following framework. The proposed solution consists of five execution steps, as shown in *Fig. 2*.

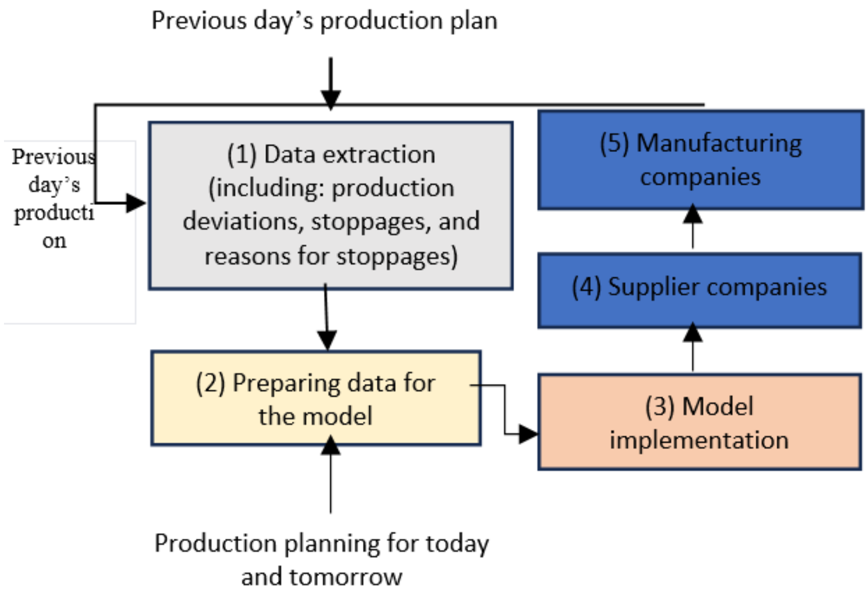

Fig. 2. A solution to improve supply chain performance.

Step 1. Data extraction

In *Step 1*, deviations and production stoppages, along with their reasons, are extracted using the production plan from the previous day and the actual production that occurred on that day.

Step 2. Preparing data for model use

Based on the information from the *Phase 1* of the research, it is expected that daily supplies have been unfairly managed, leading to shortages of some components and excess inventory of others. In *Step 2*, the supply status from the previous day is determined using the extracted data from *Step 1*. Additionally, the production plan for today and tomorrow will provide the necessary information for implementing the model.

Step 3. Model implementation

In this research, a neural network is used for modeling in order to make decisions regarding component orders. A neural network is a computational model designed to mimic the functioning of the human brain. These networks consist of a set of processing units called "Neurons," organized in layers. Neural networks typically include three types of layers:

- *Input layer: This layer receives the initial information into the network.*
- *Hidden layers: These layers perform more complex processing and can consist of multiple layers.*
- *Output layer: The final processing results are produced in this layer.*

Neural networks are trained using learning algorithms, such as supervised or unsupervised learning. In this process, the network adjusts its weights and parameters using training data to provide the best predictions or classifications.

Step 4. Transferring information and model outputs to suppliers

In *Step 4* of the research, information is sent to the supplying companies so that necessary actions can be taken.

Step 5. Sending parts to manufacturing companies

In the final step, it is expected that the suppliers will distribute the parts using the received information to improve the performance of the supply chain.

4 | Results of the Phase 1 (Supply Chain Performance Assessment)

In this section, the results of the two-way ANOVA test applied to the data in 9 scenarios are presented.

Scenario 1. Comparison of the average daily production loss ratio for the Saipa group

Null hypothesis: Equality of the average daily production loss ratio for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 1*: The Null hypothesis is rejected.

Table 1 presents the result of the two-way ANOVA for this scenario.

Table 1. Comparison of the average daily production loss ratio for the Saipa group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	14.522	0.133	1.7367	3.685E-05	1.2657
Columns	4.7814	0.956	12.448	1.885E-11	2.2355
Error	41.865	0.076			
Total	61.169				

Scenario 2. Comparison of the average weekly production loss ratio for the Saipa group

Null hypothesis: Equality of the average weekly production loss ratio for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 2*: The Null hypothesis is rejected.

Table 2 presents the result of the two-way ANOVA for this scenario.

Table 2. Comparison of the average weekly production loss ratio for the Saipa group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	0.1552	0.039	4.0644	0.0143	2.8661
Columns	0.3567	0.0714	7.4789	0.0005	2.7109
Error	0.1909	0.0096			
Total	0.703				

Scenario 3. Comparison of the average monthly production loss ratio for the Saipa group

Null hypothesis: Equality of the average monthly production loss ratio for the saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 3*: The Null hypothesis cannot be rejected for the rows, meaning the equality of the average monthly production loss ratios cannot be rejected.

However, the Null hypothesis of equality among the average monthly production loss ratios for the six Saipa companies is rejected. *Table 3* presents the result of the two-way ANOVA for this scenario.

Table 3. Comparison of the average monthly production loss ratio for the Saipa group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	9.0876	0.4327	1.6481	0.057	1.683
Columns	1.7621	0.4405	1.678	0.163	2.480
Error	22.056	0.2626			
Total	32.906				

Scenario 4. Comparison of the average daily production loss ratio under the responsibility of the Megamotor Company for the Saipa group

Null hypothesis: Equality of the average daily production loss ratio under the responsibility of the Megamotor Company for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 4*: The Null hypothesis is rejected.

Table 4 presents the result of the two-way ANOVA for this scenario.

Table 4. Comparison of the average daily production loss ratio under the responsibility of the megamotor company for the Saipa group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	28.638	0.260	1.5479	0.002	1.2688
Columns	8.14	2.035	12.0992	2.44E-09	2.3922
Error	74.06	0.1682			
Total	110.78				

Scenario 5. Comparison of the average weekly production loss ratio under the responsibility of the Megamotor Company for the Saipa group.

Null hypothesis: Equality of the average weekly production loss ratio under the responsibility of the Megamotor Company for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 5*: The Null hypothesis cannot be rejected.

Table 5 presents the result of the two-way ANOVA for this scenario.

Table 5. Comparison of the average weekly production loss ratio under the responsibility of the megamotor company for the Saipa group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	10.798	0.5142	1.2661	0.2153	1.657
Columns	4.7608	0.9521	2.3445	0.0462	2.3008
Error	42.641	0.4061			
Total	58.201				

Scenario 6. Comparison of the average monthly production loss ratio under the responsibility of the Megamotor Company for the Saipa group.

Null hypothesis: Equality of the average monthly production loss ratio under the responsibility of the Megamotor Company for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 6*: The Null hypothesis cannot be rejected.

Table 6 presents the result of the two-way ANOVA for this scenario.

Table 6. Comparison of the average monthly production loss ratio under the responsibility of the megamotor company for the Saipa group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	49.032	2.335	1.092	0.38	1.7259
Columns	10.065	3.355	1.568	0.206	2.750
Error	134.77	2.139			
Total	193.87				

Scenario 7. Comparison of the average daily production loss ratio under the responsibility of the Sazehgostar Company for the Saipa group.

Null hypothesis: Equality of the average daily production loss ratio under the responsibility of the Sazehgostar Company for the saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 7*: The Null hypothesis is rejected.

Table 7 presents the result of the two-way ANOVA for this scenario.

Table 7. Comparison of the average daily production loss ratio under the responsibility of the Sazehgostar Company for the Saipa Group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	3.051	0.763	1.654	0.225	3.259
Columns	2.526	0.842	1.826	0.196	3.49
Error	5.534	0.462			
Total	11.111				

Scenario 8. Comparison of the average weekly production loss ratio under the responsibility of the Sazehgostar Company for the Saipa group.

Null hypothesis: Equality of the average weekly production loss ratio under the responsibility of the Sazehgostar Company for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 8*: The Null hypothesis cannot be rejected.

Table 8 presents the result of the two-way ANOVA for this scenario.

Table 8. Comparison of the average weekly production loss ratio under the responsibility of the Sazehgostar Company for the Saipa Group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	0.127	0.0318	0.404	0.80	3.0069
Columns	0.237	0.0591	0.75	0.572	3.0069
Error	1.262	0.0789			
Total	1.626				

Scenario 9. Comparison of the average monthly production loss ratio under the responsibility of the Sazehgostar Company for the Saipa group.

Null hypothesis: Equality of the average monthly production loss ratio under the responsibility of the Sazehgostar Company for the Saipa group

Alternative hypothesis: Existence of a significant difference in at least one of these averages

Result of the statistical test for *Scenario 9*: The Null hypothesis cannot be rejected.

Table 9 presents the result of the two-way ANOVA for this scenario.

Table 9. Comparison of the average monthly production loss ratio under the responsibility of the Sazehgostar Company for the Saipa Group.

Source of Variation	SS	MS	F	P-Value	F Crit
Rows	35.562	0.039	4.0644	0.0143	2.8661
Columns	5.226	0.0714	7.4789	0.0005	2.7109
Error	93.667	0.0096			
Total	134.46				

Discussion and conclusion of Phase 1 of the research

In this study, the comparison of the overall average production loss for the companies over three time periods (Daily, weekly, and monthly) has led to the rejection of the Null hypothesis. It can be concluded that the impact of parts shortages on production varies across all companies, indicating the need for a more thorough investigation and the implementation of appropriate measures to improve production performance.

Furthermore, the results of the two-way ANOVA test have shown that the production losses due to parts shortages, attributed to the two leading suppliers for the six companies in the Saipa group, differ across the three time periods: daily, weekly, and monthly. This suggests that the impact of these parts shortages on production depends on the time frame being analyzed.

Since the null hypothesis regarding daily production loss has been rejected, while it has been accepted for monthly and weekly production losses, it can be inferred that the effect of parts shortages on production may change over time. This insight could assist managers and decision-makers in considering appropriate strategies for managing and controlling parts shortages.

Given that the daily production loss due to parts shortages, attributed to the two suppliers for the six companies, has been found to be significant, and the null hypothesis in this case has been rejected, this may indicate that the performance of one or both suppliers during this period may not have been satisfactory.

5 | Results of the Phase 2 (Improving Supply Chain Performance)

In this research, a neural network is employed as a modeling technique to facilitate decision-making regarding component orders. A critical aspect of this methodology is hyperparameter tuning, which involves identifying the optimal set of hyperparameters to enhance the model's performance. To systematically explore combinations of hyperparameters, techniques such as Grid Search and Random Search are utilized. These approaches facilitate the identification of the most effective hyperparameter configurations, with tools like Scikit-learn and Keras Tuner serving to streamline the process.

To evaluate the model's performance on validation data, specific performance metrics are defined, including Mean Squared Error (MSE) and Mean Absolute Error (MAE). These metrics are monitored throughout the tuning process to guide the selection of hyperparameters effectively. The analysis of the tuning results is conducted to ascertain which hyperparameters yield the best performance. The following hyperparameters are tuned in this research:

Learning rate (α): The learning rate is a crucial parameter that determines the step size during each iteration while optimizing the loss function. A common strategy is to employ grid search or random search methods to evaluate various learning rates, typically within the range of 0.001 to 0.1.

Batch size: This parameter defines the number of training samples utilized in a single iteration. Commonly tested batch sizes include 16, 32, 64, and 128. The choice of an optimal batch size can significantly influence both the training speed and the convergence of the model.

Dropout rate (p): The dropout rate specifies the fraction of neurons to be deactivated during training. A typical range for testing is between 0.1 and 0.5. The use of dropout is instrumental in mitigating overfitting by preventing complex co-adaptations within the training data.

Number of Epochs: This parameter indicates the total number of complete passes through the training dataset. While a higher number of epochs may improve the training outcome, it also carries the risk of overfitting. To counteract this, early stopping techniques are implemented to cease training when the validation loss begins to rise.

Activation functions: Various activation functions, such as ReLU, Leaky ReLU, and Tanh, are assessed in the hidden layers to determine which function yields optimal performance for the specific dataset.

Optimizer: Different optimization algorithms, including SGD, Adam, and RMSprop, are tested to identify the most effective method for minimizing the loss function.

This comprehensive approach to hyperparameter tuning ensures that the neural network model is finely tuned to achieve the best performance in making informed decisions regarding component orders. The architecture of the network used in this research is presented in *Table 10*.

Table 10. Neural network architecture.

Layer (Type)	Output Shape	Param #
dense_283 (Dense)	(None, 64)	448
dropout_38 (Dropout)	(None, 64)	0
dense_284 (Dense)	(None, 25)	1,625
dropout_39 (Dropout)	(None, 25)	0
dense_285 (Dense)	(None, 10)	260
dense_286 (Dense)	(None, 6)	66

Total params: 2399 (9.37 KB)
Trainable params: 2399 (9.37 KB)
Non-Trainable params: 0 (0.00 B)

This model was run for ten consecutive days, and the evaluation metric values for each day are presented in *Table 11*. Additionally, the chart showing the average predicted values and the actual required values of the components is displayed in *Fig. 3*.

Table 11. Evaluation criteria values for each day.

Day	Mean Squared Error	Mean Absolute Error
1	9962.970	89.671
2	32953.819	163.685
3	31447.830	158.185
4	8748.150	83.345
5	44288.647	193.899
6	44631.257	190.907
7	13442.627	99.721
8	15572.014	116.888
9	8187.547	83.882
10	11083.589	96.993
Average	22031.85	127.7176

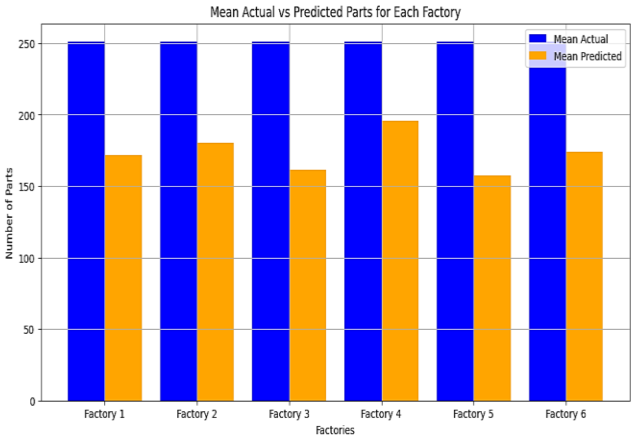

Fig. 3. Comparison of average predicted values and average actual values.

6 | Discussion and Conclusion

The present research examines the fairness of the supply chain in the Saipa automotive group and the impact of supplier performance on the distribution of components within this group. The results of the statistical analyses indicate that component shortages and the varying performance of suppliers influence production deviations and stoppages in various companies. Given the rejection of the null hypothesis regarding daily production decline and its acceptance in weekly and monthly intervals, it can be concluded that the impact of component shortages on production varies over time and requires more precise management.

The findings suggest that the performance of key suppliers, namely Megamotor and Sazehgostar, in supplying automotive parts has not been fair, which can lead to inequalities in the distribution of components among the companies in the Saipa group. Therefore, it seems essential to provide solutions for improving supply chain performance. The decision-making framework based on neural networks introduced in this research can serve as an effective tool for analyzing and predicting component supply needs, potentially enhancing supply chain performance.

Ultimately, by implementing the proposed five-step process, from information extraction to component delivery, it is expected that supply chain performance will improve and existing inequalities will be reduced. This research can assist managers and decision-makers in adopting better strategies for supply chain management by gaining a clearer understanding of supplier conditions and their impact on production, ultimately leading to increased efficiency and reduced costs within the Saipa automotive group.

Suggestions for future research include: 1) examining various factors that may affect supplier performance, including the quality of raw materials, production capacity, and supply chain management; 2) utilizing more advanced machine learning and deep learning models to predict supply needs and identify supplier behavior patterns. These models could include more complex neural networks or reinforcement learning algorithms; 3) conducting research on identifying and assessing risks present in the supply chain and their impact on supplier performance; and finally, 4) designing and developing data-driven decision-making frameworks to improve supply chain performance, focusing on the use of real data and advanced analytics.

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