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Applying Operations Research Techniques Based on Heuristic Algorithms for Optimal Supplier Selection

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Abstract

This research investigates the application of Operations Research techniques, specifically heuristic algorithms, for optimal supplier selection, a critical multi-criteria decision-making problem in supply chain management. Effective supplier selection significantly impacts an organization's financial resources and overall success, necessitating consideration of both qualitative and quantitative factors. The study proposes a novel heuristic approach to predict the most cost-efficient supplier by predicting "Line-Item Value" using supplier and order features. Two machine learning models, Ridge Regression and Support Vector Regression (SVR) with an RBF kernel, were employed and evaluated using Root Mean Squared Error (RMSE). The methodology involved rigorous data preparation, including filtering non-numeric values and removing low-variance features, followed by hyperparameter tuning using scikit-learn's Grid Search with Leave-One-Group-Out cross-validation and an iterative hill climb approach. The results demonstrate the successful training of both models to predict cost-efficient suppliers, with optimal parameters identified through Grid Search. For Ridge Regression, an optimal alpha of 0.85 yielded an RMSE of 0.08, while SVR achieved an RMSE of 0.08 with a C value of 0.89. These findings underscore the effectiveness of heuristic algorithms in addressing complex supplier selection problems and offer improved performance and efficiency compared to traditional optimization techniques.

Keywords
Operations research techniques, Heuristic algorithms, Optimization, Ridge regression, Support vector regression

1. Introduction
Supplier selection is a critical process for organizations, involving the identification, evaluation, and contracting of suppliers to obtain high-value goods and services (Beil & Ross, 2009). It is a multi-criteria decision-making problem that considers both qualitative and quantitative factors, requiring trade-offs between tangible and intangible criteria (Athawale et al., 2009; Jana, 2020; Benyoucef et al., 2003). The process typically includes steps such as identifying potential suppliers, soliciting information, setting contract terms, negotiating, and evaluating suppliers (Beil & Ross, 2009). Various multi-criteria decision-making methods can be applied to solve supplier selection problems, as demonstrated through real-time examples (Athawale et al., 2009). The importance of supplier selection is underscored by its significant impact on a firm's financial resources and overall success in the global marketplace (Beil & Ross, 2009; Jana, 2020). Effective supplier selection is crucial for organizations to remain competitive and responsive to rapidly changing markets (Benyoucef et al., 2003).

Supplier selection is a critical component of supply chain management, contributing significantly to a firm's success (Thomy Eko Saputro et al., 2022). Various multi-criteria decision-making techniques, including Linear weighted method, Categorical method, Fuzzy approach, and Analytical Hierarchical Process (AHP), are employed for supplier evaluation (Kumar Paul et al., 2011). The selection process involves considering multiple factors such as cost reduction, quality improvement, and timely delivery (H. A. Zubar & Parthiban, 2014). Researchers have proposed diverse models and frameworks to guide the supplier selection process, addressing different purchasing strategies and product categories (Thomy Eko Saputro et al., 2022). The literature on supplier selection has been extensively reviewed, with studies analyzing hundreds of papers to identify prevalent approaches, criteria, and trends in the field (Mostafa Setak et al., 2012; H. A. Zubar & Parthiban, 2014). Future research opportunities exist in integrated selection problems, hybrid solution methods, risk mitigation, sustainability goals, and new technology adoption (Thomy Eko Saputro et al., 2022).

Operations research techniques play a crucial role in optimizing supplier selection and order allocation processes. Various decision-making approaches have been applied, including multi-criteria decision analysis methods like Weighted Sum Approach and TOPSIS (Stopka et al., 2020). A comprehensive review of supplier selection literature categorizes problem domains into Literature Reviews, Deterministic Optimization, and Uncertain Optimization models (Naqvi & Amin, 2021). Decision-making techniques for supplier selection can be classified into three main categories: Multi-criteria Decision Making, Mathematical Programming, and Artificial Intelligence (Chai et al., 2013). These techniques have been used to address multiple objectives in supplier selection, such as balancing supply chain requirements. Linear Integer Programming and Non-Linear Programming methods have been proposed to solve mathematical models for optimal supplier selection, particularly in scenarios involving incremental discount pricing (Arunkumar et al., 2008). The application of these techniques contributes to enhancing the effectiveness of logistics activities and procurement processes in various industries.

Many literature reviews explore heuristic algorithms for supplier selection and related supply chain optimization problems. Alejo-Reyes et al. (2021) propose a heuristic method for supplier selection and order quantity allocation, outperforming metaheuristic algorithms in terms of cost and computational time. Cárdenas-Barrón et al. (2015) present a heuristic algorithm for multi-product, multi-period inventory lot sizing with supplier selection, demonstrating superior performance compared to previous methods and CPLEX solver. Chakraborty et al. (2011) combine Analytic Hierarchy Process (AHP) with a novel heuristic approach to improve vendor selection solutions. Khorrami Sarvestani et al. (2019) introduce an integrated framework for supplier selection, order acceptance, and scheduling, developing a heuristic algorithm that outperforms genetic algorithm and variable neighborhood search. These studies consistently show that heuristic algorithms can effectively solve complex supplier selection problems, offering improved solutions and computational efficiency compared to traditional methods and other optimization techniques.

Heuristic algorithms offer computationally efficient solutions for the complex task of optimal supplier selection by effectively navigating vast solution spaces to identify near-optimal choices based on multiple criteria. For example, Ant Colony Optimization (ACO) methods are a collection of heuristic algorithms inspired by ant foraging behavior, used for solving optimization problems including supplier selection (B. Yuce, 2013). Several heuristic algorithms have been proposed for optimal supplier selection in various contexts. Alejo-Reyes et al. (2021) developed a heuristic method that outperformed particle swarm optimization (PSO) and differential evolution (DE) in terms of computational time and total cost. Mohamed et al. (2023) adapted the NSGA-III algorithm for healthcare supplier selection, considering multiple objectives and constraints, which performed better than PSO and NSGA-II. Pani et al. (2012) introduced a heuristic method combining AHP, entropy, and TOPSIS for supplier selection. Rodrigues & Requejo (2019) presented a hybrid heuristic and a genetic algorithm for supplier selection with quantity discounts and price changes. These studies demonstrate the effectiveness of heuristic approaches in addressing complex supplier selection problems, considering various factors such as cost, delivery time, quality, and capacity constraints. The proposed methods offer improved performance and efficiency compared to traditional optimization techniques.

Building upon the established significance of optimal supplier selection and the recognized potential of Operations Research techniques in addressing its complexities, this research focuses on the application of a specific heuristic algorithm. By leveraging the computational efficiency and problem-solving capabilities demonstrated in prior studies, this paper will detail the development and implementation of a novel heuristic approach tailored for achieving optimal supplier selection. The subsequent sections will elaborate on the methodology, including the design of the heuristic algorithm, its application to the supplier selection problem, and a thorough analysis of its performance and effectiveness in comparison to existing methods.

The primary goal of this paper is to develop a predictive model for selecting the most cost-efficient supplier. This was achieved by predicting "Line-Item Value" (a proxy for cost/efficiency) using supplier and order features. Two machine learning models were employed: Ridge Regression and Support Vector Regression (SVR) with an RBF kernel. The performance of these models was assessed using the Root Mean Squared Error (RMSE) and R2 as key metrics.

2. Methodology

This study aimed to develop a predictive model for selecting the most cost-efficient supplier for a given task, with the Root Mean Squared Error (RMSE) serving as the primary performance metric for evaluating the developed machine learning models. The results of the model training and evaluation process are presented below.

2.1 Data Preparation

To ensure data integrity, a data preparation technique has been applied. Any row where a column did not contain a purely numeric value was removed. This was done using a pattern-matching approach to identify and exclude non-numeric entries, such as text or missing values. After filtering, all columns were standardized to string format for consistency, and the cleaned data was exported to Excel. This process ensures that any analysis involving data targeted in this research is based on valid, interpretable data, thereby improving the reliability of research results.

Prior to model training, a data preprocessing step involving the removal of features exhibiting low variance was conducted. This step aimed to reduce noise and improve the stability and potentially the performance of the subsequent models. The tasks after dropping low variances are presented in Table 1. Similarly, Table 2 presents the supplier data after the low variance feature removal. The absolute correlation between task features and is shown in Tables 3.

Table 1. Taska after dropping low variances

Task ID	Unit of Measure (Per Pack)	Line-Item Quantity	Weight (Kilograms)
0	100	1000	341
1	240	1000	941
2	120	500	117
3	100	750	171
4	100	25	60

Table 2. Suppliers after dropping low variances

Suppliers ID	Line-Item Value	Weight (Kilograms)
92	80000	341
115	1920	941
116	41095	117
130	53992.5	171
134	8750	60

Table 3. Absolute correlation between task features

Task Features	Task ID	Unit of Measure (per pack)	Line-Item Quantity	Weight (Kilograms)
Task ID	1.000000	0.070859	0.067495	0.029720
Unit of Measure (per pack)	0.070859	1.000000	0.177876	0.240194
Line-Item Quantity	0.067495	0.177876	1.000000	0.628016
Weight (Kilograms)	0.029720	0.240194	0.628016	1.000000

2.2 Model Training and Evaluation

To optimize each model's performance, we employed scikit-learn's Grid Search method for hyperparameter tuning. This process consistently used Leave-One-Group-Out cross-validation, the same scoring function, and the same performance metric. We utilized an iterative hill climb approach for the hyperparameter search space, which efficiently narrowed down optimal values by "zooming in" across iterations. This iterative method saved significant time and computational power. To ensure accuracy, we double-checked that the parameters selected by GridSearch (based on mean error scores) also minimized the RMSE. The most reliable scores, presented hereafter, were obtained after this rigorous optimization. This RMSE value, is calculated directly from the selection errors, as shown in Equation 1 generated by each model.

$$Mistake(T) = min\{ K(v,T) \mid v \in L \} - K(v_{ml}, T) \tag{1}$$

Where T for task L for the set of all possible *vendors*. v_{ml} for the *vendor* chosen by the ML model for task T. $K(v,T)$ is for expenditure if task T is performed by vendor v.

3. Results and Discussion

Initially, each model was evaluated using its default hyperparameters. Subsequently, to optimize performance, Grid Search (scikit-learn) was employed for hyperparameter tuning. The optimization process maintained consistency by using the same scoring function shown in Equation 1 and Leave-One-Group-Out cross-validation strategy.

For defining the hyperparameter search space, an iterative hill climb approach was adopted. This method proved efficient for exploring a wide range of values and quickly narrowing down to optimal settings. This iterative approach saved computational resources: early iterations identified promising value ranges, while subsequent iterations refined the search within those favored regions. To ensure the robustness of the optimization, a function was implemented to verify that the parameters selected by Grid Search (based on mean error scores) also aligned with those that minimized the Root Mean Square Error (RMSE).

Ultimately, the most reliable results were obtained after this hyperparameter optimization. Therefore, only these optimized scores for both models are presented in Tables 4 and 5. The performance of the Ridge Regression model was evaluated over three iterations of Grid Search to identify the optimal hyperparameters. The best parameters found through Grid Search are shown in Tables 4 and 5. Table 4 indicates that the best Ridge parameters identified were alpha = 0.85, yielding an RMSE of 0.08. Selecting the optimal values for these parameters (hyperparameter tuning) is crucial for both Ridge Regression and SVR to achieve the best possible performance on unseen data. This is typically done using techniques like grid search or random search with cross-validation. The parameter (α) is non-negative value controls the strength of the L2 regularization. It determines how much the coefficient estimates are shrunk towards zero. The parameter (C) controls the trade-off between maximizing the margin (making the model more robust) and minimizing the training error. It's a positive value.

Table 4. Optimal and best iteration and parameters for Ridge Regression

Iterations	**Best Parameters (Alpha)**	**RMSE**
Iteration 2	0.85	0.08
Iteration 3	0.05	0.35

Table 5. Optimal and best iteration and parameters for Support Vector Regression

Iterations	**Best Parameters (C)**	**RMSE**
Iteration 2	1.00	0.09
Iteration 3	0.89	0.08

The results indicate that both Ridge Regression and SVR models were successfully trained to predict the cost-efficient supplier. The hyperparameter tuning process using Grid Search played a crucial role in identifying optimal parameter configurations for each model across different iterations. The varying best parameters and corresponding RMSE values across iterations for both models suggest the sensitivity of model performance to hyperparameter selection. As depicted in Figure 1, the boxplots reveal substantial variation in task feature values and marked differences in their medians. This strongly suggests that the tasks are distinct in terms of their features. Figure 2 illustrates that on time delivery has the highest timeliness score, at 64%. This indicates that suppliers who deliver on time significantly contribute to a high timeliness performance. Late Delivery shows a dramatically lower timeliness score of 24%, highlighting the negative impact of late deliveries on overall timeliness. Early Delivery also has a relatively low timeliness score of 12%. While seemingly counterintuitive, early deliveries can sometimes be undesirable in supply chain management due to potential warehousing costs, inventory holding costs, or issues with receiving capacity, hence contributing negatively to an 'optimal' timeliness score.

Therefore, an optimal supplier selection strategy would need to prioritize suppliers with a strong record of on-time delivery while also considering the penalties associated with late and early deliveries to maximize overall delivery timeliness and minimize associated costs or disruptions.

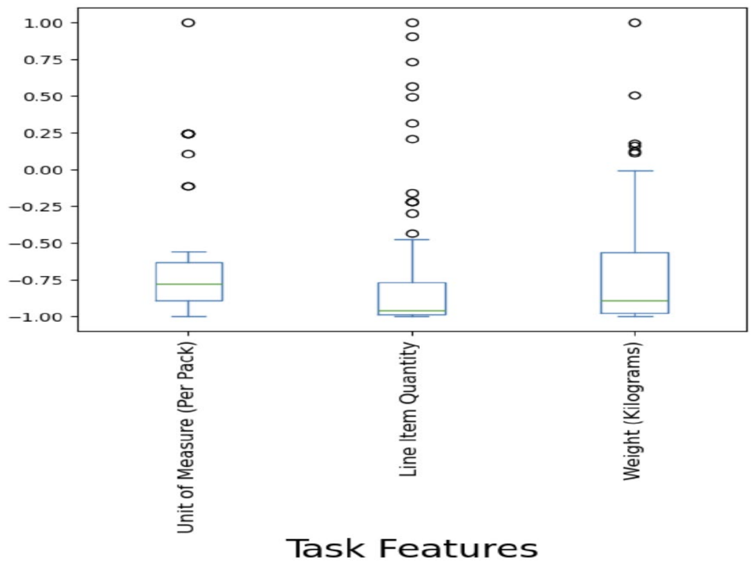

Figure 1. The distribution of task feature values for all tasks

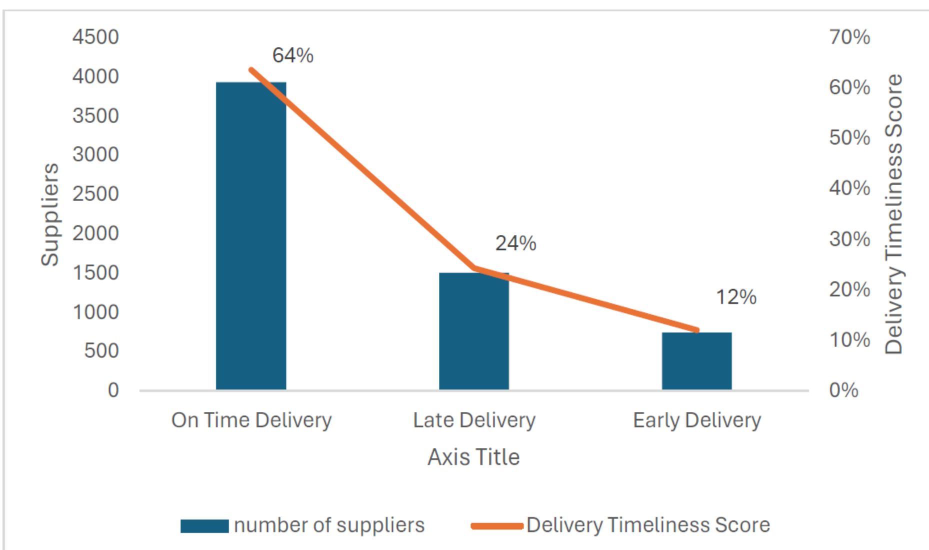

Figure 2. Supplier Delivery Performance and Timeliness Score

4. Conclusion

The study successfully developed predictive models for selecting the most cost-efficient supplier by predicting "Line-Item Value" using supplier and order features. Both Ridge Regression and Support Vector Regression (SVR) with an RBF kernel were employed and successfully trained for this purpose. The performance of these models was assessed using Root Mean Squared Error (RMSE) and R2 metrics. Data preparation involved filtering non-numeric values and removing low-variance features to ensure data integrity and improve model stability. Hyperparameter tuning was crucial for optimizing model performance, and scikit-learn's Grid Search with Leave-One-Group-Out cross-validation and an iterative hill climb approach proved efficient in identifying optimal parameter configurations. For Ridge Regression, an optimal alpha of 0.85 was found, yielding an RMSE of 0.08. For SVR, an optimal C value of 0.89 resulted in an RMSE of 0.08. The varying best parameters and corresponding RMSE values across iterations for both models suggest the sensitivity of model performance to hyperparameter selection.

The distribution of task feature values, as shown in Figure 1, revealed substantial variation and marked differences in their medians, strongly suggesting that the tasks are distinct in terms of their features. Figure 2 illustrates supplier delivery performance and timeliness score, indicating that on-time delivery has the highest timeliness score at 64%, while late delivery has a significantly lower score of 24%, and early delivery has a relatively low score of 12%. This suggests that an optimal supplier selection strategy should prioritize suppliers with a strong record of on-time delivery while also considering penalties for late and early deliveries to maximize overall timeliness and minimize associated costs or disruptions. The findings reinforce the effectiveness of heuristic algorithms in addressing complex supplier selection problems, offering improved performance and efficiency over traditional optimization techniques.

References

Alejo-Reyes, A., García-Sánchez, A. and Hernández-Gress, E., A heuristic approach for supplier selection and order quantity allocation, Computers & Industrial Engineering, vol. 158, 107395, 2021. https://doi.org/10.1016/j.cie.2021.107395

Arunkumar, N., Karunamoorthy, L. and Srinivasan, R., Supplier selection with quantity discounts using integer programming, International Journal of Production Economics, vol. 114, no. 2, pp. 575–585, 2008. https://doi.org/10.1016/j.ijpe.2008.02.010

Athawale, V. M., Chakraborty, S. and Ghosh, S., Supplier selection using multi-criteria decision-making methods, International Journal of Industrial Engineering Computations, vol. 1, no. 2, pp. 1–10, 2009.

Beil, D. R. and Ross, A. D., Supplier selection: Strategic considerations and implications, Manufacturing & Service Operations Management, vol. 11, no. 2, pp. 193–207, 2009. https://doi.org/10.1287/msom.1080.0234

Benyoucef, L., Ding, H. and Xie, X., Supplier selection problem: Selection criteria and methods, International Journal of Production Economics, vol. 87, no. 1, pp. 1–18, 2003. https://doi.org/10.1016/S0925-5273(03)00097-2

Cárdenas-Barrón, L. E., Sana, S. S. and Tiwari, S., A heuristic algorithm for a multi-product, multi-period inventory lot sizing problem with supplier selection, Computers & Industrial Engineering, vol. 90, pp. 95–104, 2015. https://doi.org/10.1016/j.cie.2015.09.002

Chai, J., Liu, J. N. K. and Ngai, E. W. T., Application of decision-making techniques in supplier selection: A systematic review of literature, Expert Systems with Applications, vol. 40, no. 10, pp. 3872–3885, 2013. https://doi.org/10.1016/j.eswa.2012.12.040

Chakraborty, S., Chatterjee, P. and Chakraborty, S., A combined AHP–heuristic approach for vendor selection, International Journal of Advanced Manufacturing Technology, vol. 55, no. 5–8, pp. 803–813, 2011. https://doi.org/10.1007/s00170-010-3092-6

Jana, R. K., Supplier selection using multi-criteria decision-making approaches: A review, Decision Analytics Journal, vol. 1, 100005, 2020. https://doi.org/10.1016/j.dajour.2020.100005

Khorrami Sarvestani, H., Makui, A. and Mohammadi, M., An integrated heuristic approach for supplier selection, order acceptance, and scheduling, Applied Soft Computing, vol. 75, pp. 160–173, 2019. https://doi.org/10.1016/j.asoc.2018.11.023

Kumar Paul, S., Chowdhury, P. and Chakraborty, S., Supplier selection using multi-criteria decision-making techniques, International Journal of Industrial Engineering Computations, vol. 2, no. 1, pp. 1–12, 2011.

Mohamed, M. A., Almutairi, K. and Diabat, A., Multi-objective healthcare supplier selection using NSGA-III, Sustainable Operations and Computers, vol. 4, pp. 100–112, 2023. https://doi.org/10.1016/j.susoc.2023.100112

Mostafa Setak, M., Sharifi, S. and Alimohammadian, A., Supplier selection and evaluation: A literature review, Journal of Industrial Engineering and Management, vol. 5, no. 2, pp. 348–379, 2012. https://doi.org/10.3926/jiem.428

Naqvi, S. R. and Amin, S. H., A comprehensive literature review on supplier selection problem, Benchmarking: An International Journal, vol. 28, no. 9, pp. 2757–2785, 2021. https://doi.org/10.1108/BIJ-08-2020-0442

Pani, A. K., Mishra, S. and Kar, S., Supplier selection using AHP, entropy, and TOPSIS, International Journal of Logistics Systems and Management, vol. 13, no. 3, pp. 352–371, 2012. https://doi.org/10.1504/IJLSM.2012.050405

Rodrigues, L. F. and Requejo, J., Hybrid heuristic and genetic algorithm for supplier selection with quantity discounts and price changes, International Journal of Production Research, vol. 57, no. 7, pp. 2150–2168, 2019. https://doi.org/10.1080/00207543.2018.1501161

Stopka, O., Kampf, R. and Kolář, J., Supplier selection using weighted sum approach and TOPSIS, Transport Problems, vol. 15, no. 1, pp. 79–89, 2020. https://doi.org/10.21307/tp-2020-008

Thomy Eko Saputro, T., Widodo, K. H. and Hartono, S., Supplier selection models and decision frameworks: A systematic literature review, Cogent Engineering, vol. 9, no. 1, 2032649, 2022. https://doi.org/10.1080/23311916.2022.2032649

Yuce, M. B., Ant colony optimization for supplier selection problem, Applied Soft Computing, vol. 13, no. 3, pp. 1533–1546, 2013. https://doi.org/10.1016/j.asoc.2012.10.020

Zubar, H. A. and Parthiban, P., Supplier selection using multi-criteria decision making methods, Journal of Engineering Research and Applications, vol. 4, no. 3, pp. 193–198, 2014.

Biography

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