Research Annals of Industrial and Systems Engineering

www.raise.reapress.com

Res. Ann. Ind. Syst. Eng. Vol. 1, No. 3 (2024) 143–159.

Paper Type: Original Article

Optimization of Human Resource Allocation Considering Customer Relationship Management Criteria and Uncertainty Conditions in Automotive Dealerships

Seyed Esmaeil Najafi[1,*], Shahab Amani[1]

[1]Department of Industrial Engineering, Faculty of Engineering, Islamic Azad University, Science and Research Branch, Tehran, Iran; najafi1515@yahoo.com; shahabamani73@gmail.com.

Citation:

Received: 13 July 2024 *Revised: 09 September 2024* *Accepted: 10 November 2024*	Najafi, S. A., Amani, Sh. (2024). Optimization of human resource allocation considering customer relationship management criteria and uncertainty conditions in automotive dealerships. *Research annals of industrial and systems engineering, 1*(3), 143-159.

Abstract

The present study employs a mixed-integer mathematical model to optimize human resource allocation in the automotive industry. The objective function of the proposed model aims to minimize the maximum waiting time of customers in service queues, while the constraints involve workforce allocation and time calculations for each service at every center. Most previous studies have relied on survey methods and interviews with experts and organizational elites. Given the complexity of designing an optimal model for Customer Relationship Management (CRM), such methods may distort the obtained results due to errors in interviews and questionnaires. Hence, this research utilizes mathematical optimization methods. For solving small-scale problems, the BARON method was applied using GAMS software. Due to the NP-hard nature of the allocation problem, metaheuristic algorithms were employed to handle larger-scale cases. Since these algorithms are designed based on natural elements, a stochastic procedure was implemented to generate initial solutions and enhance the final solution process. Thus, appropriate comparisons must be conducted to ensure the accuracy of such a procedure. To this end, three metaheuristic algorithms – Genetic Algorithm (GA), Harmony Search, and Grey Wolf Optimizer (GWO)–were employed to solve the final problem. The computational results indicated that the GOW outperformed the other algorithms in terms of efficiency, making it more practical for solving real numerical instances.

Keywords: Customer relationship management, Mathematical optimization, Metaheuristic algorithms, Automotive industry.

1 | Introduction

Researchers and managers in industrial and service organizations have made extensive efforts to improve performance management tools and develop a customer-oriented approach, highlighting the significance of customer satisfaction in organizational success. The necessity of utilizing information technology compels organizations to equip themselves with the technical knowledge and skills required to understand customer needs and enhance the quality of their services and products.

Corresponding Author: najafi1515@yahoo.com
https://doi.org/10.22105/raise.v1i3.55

Customer Relationship Management (CRM) consists of activities that enhance an organization's value chain, covering aspects such as cost savings, quality improvement, flexibility, and increased employee competence. CRM makes manufacturers more responsive to customer needs and improves product quality. Retaining existing customers is more crucial than acquiring new ones, and an effective customer relationship program can enhance customer satisfaction and boost organizational revenue. Teamwork is vital in CRM processes, facilitating quicker problem resolution and improving service quality. Many organizations employ CRM to drive business transformation and acknowledge its effectiveness in customer retention, especially as technology reshapes customer interactions.

Iran Khodro, leveraging its various dealerships, provides customer services; however, due to working hour limitations and staff constraints, the services received by customers often fail to align with their diverse preferences and needs. While some customers visit dealerships immediately, others delay their visits until a significant issue arises. Iran Khodro seeks to improve customer relations and increase efficiency, believing retaining current customers is more cost-effective than attracting new ones. One of the significant challenges in CRM is the absence of defined models for implementing and evaluating these strategies. Each organization operates within its unique culture and processes, making a universal solution impractical. Maintaining continuous customer interaction to boost sales and reduce costs is another critical aspect of CRM.

Existing research in this field has focused on optimizing CRM through data mining; however, the results have not been satisfactory. This study aims to design a mathematical model based on metaheuristic algorithms, emphasizing parameter uncertainty to introduce a novel approach to CRM. Customer needs are identified and categorized through questionnaires, and then personnel distribution is optimized accordingly. New processes and methods for training individuals with advanced skills are evolving, transforming personal information into collective knowledge. The primary challenge of this century is the efficient recording and easy access to this information. Effective implementation of CRM can enhance organizational awareness and, consequently, increase revenue by optimizing resource allocation and responding effectively to customer demands.

Human resource management is another critical aspect of this process, encompassing recruitment, training, and employee retention, all directly impacting CRM. Particularly in after-sales service dealerships such as Iran Khodro, the importance of optimal workforce allocation, guided by optimization methods while considering CRM criteria and uncertainty conditions, becomes evident. A structure based on mathematical programming methods can be employed to optimize human resource allocation in automotive company dealerships. The current study examines CRM criteria and uncertainty conditions, analyzing their effects on the responses to the following questions:

I. Considering CRM criteria and uncertainty conditions, how can a structure based on mathematical programming methods be developed to optimize human resource allocation in automotive company dealerships?

II. What impact does accounting for uncertainties in the problem have on the analysis of the obtained responses?

III. How can proper human resource allocation improve CRM?

IV. What effect do metaheuristic algorithms have on the final responses in terms of solution time and quality?

Mathematical programming methods can be utilized to optimize workforce allocation in automotive company dealerships. This study explores CRM criteria and uncertainty conditions, analyzing their influence on the obtained results. One of the primary objectives of this research is to assess the impact of proper human resource allocation on improving CRM. Furthermore, the study examines metaheuristic algorithms as an optimization approach to evaluate their effects on solution time and response quality. The objectives of this research are as follows:

I. Developing a mathematical programming-based structure for optimizing human resource allocation while considering CRM criteria and uncertainty conditions.

II. Analyzing the impact of accounting for uncertainties on the analysis of the obtained responses.

III. Evaluating how appropriate workforce allocation contributes to improved CRM.

IV. Investigating the effects of using metaheuristic algorithms on final responses in terms of solution time and quality.

Based on conducted reviews, no prior research has proposed an approach integrating mathematical programming methods and metaheuristic algorithms for human resource allocation while incorporating CRM criteria. Besides, previous studies have overlooked the use of robust programming to address uncertainty conditions. The development of diverse solution algorithms and the comparative analysis of their results represent another innovative aspect of this study.

2 | Literature Review

Organizations plan to understand their external environment and achieve short-term and long-term goals, leveraging experiential knowledge and human resource capabilities. In today's world, organizations are highly dependent on human capital, which is considered their most valuable asset. Human resources are critical in decision-making, problem-solving, and productivity enhancement. Optimal resource allocation is a crucial tool for executing strategies and long-term programs, with organizational success hinging on this allocation's quality and precise control.

In service organizations, human resource management and its optimal allocation hold particular significance, as competitiveness and organizational sustainability depend on having the right individuals at the right place and time. To gain insights into this subject, five studies on CRM, three studies on uncertainty, three on Data Envelopment Analysis (DEA), three on metaheuristic algorithms, four on Knowledge Management (KM), and two on the automotive industry were thoroughly reviewed. The objectives and findings of each study will be discussed in the following sections.

Qazi et al. [1] examined the impact of organizational commitment and KM on CRM and, consequently, their effects on profitability and customer loyalty through customer satisfaction and brand image moderation. The findings indicate that KM and organizational commitment, directly and indirectly, influence profitability and customer loyalty. Moreover, brand image moderates the relationships between CRM and other variables. This study suggests that telecommunications companies should adopt effective CRM strategies to enhance profitability and customer loyalty.

Maleki et al. [2] investigated the effect of social CRM on customer satisfaction and loyalty. Their results reveal that while traditional CRM and social media technologies contribute to increased customer satisfaction, only traditional CRM directly affects customer loyalty. Customer satisfaction also plays a mediating role in this relationship. The study recommends that automotive companies in developing countries implement effective social CRM strategies to improve customer satisfaction and loyalty.

Khenizer et al. [3] explored the economic and managerial implications of AI-powered chatbots in CRM systems. Qualitative interviews with experts indicated that these chatbots reduce costs, enhance efficiency, and improve human performance across various industries. However, ethical concerns impose limitations on their use in healthcare. This study contributes to a deeper understanding of how AI chatbots affect customer interactions, streamline business processes, and influence organizational strategies.

Nwabeke et al. [4] focused on marketing, analyzing its implementation challenges and practical applications. Integrating data analytics and CRM tools is a crucial factor for the success of digital marketing strategies.

Lilola et al. [5] examined the impact of artificial intelligence on customer engagement and CRM in Small and Medium Enterprises (SMEs). Key technologies such as machine learning, natural language processing, and predictive analytics improve customer engagement by enabling personalized interactions, automating routine tasks, and providing deep insights. The main challenges include costs, integration complexities, and the need for technical expertise.

Durbiano et al. [6] addressed the rising concentration of atmospheric Carbon Dioxide (CO2), a primary driver of the greenhouse effect and global warming. To monitor this situation and provide reliable emission data to governments, gas reference materials CRMs are needed for atmospheric CO_2 concentrations. This study describes two independent metrological traceability routes for producing these CRMs and presents a method for evaluating uncertainty related to CRM stability, ensuring no significant trends over time. These CRMs serve as an intermediate step in developing a new generation of CRMs featuring certified isotopic composition.

Liao et al. [7] investigated the impact of customer stability on debt costs and the moderating role of environmental uncertainty. The findings indicate that customer stability significantly reduces debt costs, with this effect intensifying as environmental uncertainty increases. Furthermore, industry competition, customer concentration, and average customer age strengthen this relationship. This study highlights the importance of CRM and supply chain risk management and offers future research directions.

Shi et al. [8] proposed a new method for estimating uncertainty in semi-supervised medical image segmentation. They introduced a novel model called the Conservative-Radical Network (CoraNet), consisting of three main components: The Conservative-Radical Module (CRM), the Certain-Segment Network (C-SN), and the Uncertain-Segment Network (UC-SN). This method was evaluated on various datasets and demonstrated superior performance compared to existing techniques. The study also analyzed the connections and differences between this model and conventional uncertainty estimation approaches.

De Oliveira [9] examined three widely used decision-making techniques–DEA, Multi-Criteria Decision Analysis (MCDA), and Cluster Analysis (CA)–that help decision-makers find optimal solutions to problems involving multiple and often conflicting criteria. This study comprehensively reviews the literature on DEA, MCDA, and CA models to identify current and potential applications and future development trends. The methodi ordinatio approach was used to determine the most influential papers across three databases: Scopus, sciencedirect, and web of science. Since no studies were found combining all three techniques simultaneously, the study examined their pairwise combinations. The findings indicate that 43.87% of the 490 reviewed papers combined DEA and MCDA techniques to analyze efficiency and productivity issues.

Kheyri et al. [10] conducted a comparative evaluation of Iran's automotive industry, focusing on performance assessment of after-sales service dealerships. Their proposed model improves the accuracy and practicality of comparative evaluations by considering repair indices and customer satisfaction. The DEA model was applied to evaluate 20 dealerships, and the results demonstrated that the proposed conditions significantly enhanced assessment accuracy. The study also discusses the importance of dependent parameters in comparative evaluation.

Wichapa et al. [11] introduced an innovative hybrid method called DEAV-Taguchi, which integrates DEA with the Taguchi method to solve Multi-Response Optimization (MRO) challenges. Using two case studies, this approach demonstrated improved optimization accuracy and performance. The study aims to develop a robust optimization framework for modern manufacturing processes and anticipates future applications for various materials and production methods while assessing their economic and environmental impacts.

Dehghani et al. [12] introduced the Cuckoo Optimization Algorithm (COA), inspired by cuckoo behavior in hunting iguanas and escaping predators. COA was modeled into exploration and exploitation phases, and its performance was evaluated using 51 objective functions and four real-world optimization problems. The results indicate that COA outperforms 11 other metaheuristic algorithms by balancing global and local search capabilities.

Albayk et al. [13] developed the Pufferfish Optimization Algorithm (POA) inspired by pufferfish's defensive behavior against predators. POA was structured in exploration and exploitation phases and tested on the CEC 2017 benchmark suite. Results show that POA efficiently balances exploration and exploitation, achieving effective solutions. Its real-world applicability was confirmed by evaluating 22 constrained optimization problems from CEC 2011 and four engineering design challenges, demonstrating its strong performance in practical scenarios.

Hubalovska et al. [14] introduced the Botox Optimization Algorithm (BOA), inspired by Botox's working mechanism. Designed for optimization tasks, BOA leverages human-inspired techniques. Evaluations show that BOA successfully balances exploration and exploitation, outperforming 12 well-known metaheuristic algorithms on various benchmark functions. BOA's effectiveness in solving constrained optimization problems was further validated through its application to the CEC 2011 benchmark set.

Khosravi et al. [15] analyzed measurement uncertainty in standard material and compound evaluations within physicochemical measurements. Material purity plays a crucial role in studying their properties, especially when using pure substances as comparison standards. A comprehensive study of pure materials is essential for metrological applications and analytical research, as traceable measurement systems rely on materials with certified content and well-defined uncertainties.

Jayeskara et al. [16] examined the mediating role of KM and CRM between Customer Orientation (CO) and Technological Capabilities (TC) in Sri Lanka's travel agency sector. The results indicate that KM and CRM do not act as direct mediators for CO or TC. The findings suggest that tourism managers in Sri Lanka should focus on direct customer engagement and technology adoption rather than relying solely on KM and CRM. This study also highlights new research opportunities for enhancing public trust and resilience in Sri Lanka's post-pandemic tourism industry.

Chaitanipat [17] examined Customer Knowledge Management (CKM) in SMEs, emphasizing how customers transition from passive recipients to active knowledge partners. Despite the popularity of entrepreneurship and SMEs in economic development, research on CKM in this context is limited and fragmented. This study provides a comprehensive literature review of related concepts such as knowledge-centered leadership, trust in management, and firm performance, offering a holistic view of CKM in SMEs and proposing a future research agenda.

Zia et al. [18] explored the relationship between CRM, Knowledge Management Processes (KMP), and the capacity for product and service innovation. Data from 88 businesses in China and 287 survey responses were analyzed. The findings indicate that CRM significantly influences KM. The CKM process integrates innovation capacity with CRM, offering insights for executives to better understand the interactions among customers, knowledge, and innovation.

Al Zahra et al. [19] analyzed CRM implementation strategies for enhancing customer loyalty at Tuna Toyota Silgon, a company that sells Toyota cars, spare parts, vehicle services, and test drives. The results indicate that effective CRM implementation contributes to increased customer loyalty. This qualitative study employed interviews, observations, and document analysis.

Ho et al. [20] investigated how automotive companies integrate CRM tools and Big Data Analytics (BDA) into their marketing strategies to enhance Total Quality Management (TQM) post-COVID-19. Through qualitative research and interviews with 18 companies, the findings suggest that CRM technology adoption improves business performance and strengthens digital culture. The study also explores challenges in implementing CRM and BDA. However, generalization is limited due to the small sample size. The findings propose customer-centric approaches and new opportunities in the automotive industry.

3 | Research Methodology

3.1 | Modeling and Problem Solving Algorithms

Questionnaires are utilized to identify and classify customer needs, where customers are categorized based on the average importance of parameters such as cost, time, quality, etc. However, a metaheuristic algorithm is applied to allocate personnel based on customer needs optimally. The mathematical model of the problem is presented as follows:

3.1.1 | Mathematical model

Table 1. Sets and notations of the mathematical model.

Sets and Notations		
I	Set of centers	$\{i \vert i = 1,2,3, \ldots \vert I \vert\}$
J	Set of services available at the centers	$I = \{j \vert j = 1,2,3, \ldots \vert J \vert\}$

Table 2. Parameters and variables of the mathematical model.

Parameters		Variables	
D_{ij}	The average demand for service j at active center i	N_{ij}	The number of personnel required to perform service j at active center i
T_j	The time required to perform service j	X_{ij}	The average waiting time of customers to receive service j at the center i
AW_j	The number of specialists available to perform service j	C_i	The average waiting time of customers at the center i
AT_j	The available time of specialists for service j		

$$\text{Min } Z = \max_{i \in I}\{C_i\}, \tag{1}$$

s. t.

$$\text{For all } i \in I, j \in J, \ D_{ij}\, T_j \leq AT_j\, N_{ij}, \tag{2}$$

$$\text{For all } i \in I, j \in J, \ X_{ij} = \frac{D_{ij}\, T_j}{N_{ij}}, \tag{3}$$

$$\text{For all } i \in I, \ C_i = \sum\nolimits_{j \in J} X_{ij}, \tag{4}$$

$$\text{For all } j \in J, \ \sum\nolimits_{i \in I} N_{ij} \leq AW_j. \tag{5}$$

As observed, the objective function aims to minimize the maximum customer waiting time at service centers.

Constraint (2) calculates the required workforce for each center based on the type and volume of services demanded. Here, the total service time on the left side determines the number of personnel needed, considering the available working time on the right side.

Constraint (3) computes the average waiting time per service per center. According to this constraint, the waiting time is determined by the total required service time divided by the number of hired personnel at that dealership.

Constraint (4) calculates each center's total customer waiting time across all services.

Constraint (5) ensures that the total number of hired specialists across all centers does not exceed the available workforce within the organization.

Since some problem parameters are subject to uncertainty, the robust optimization model is formulated in two approaches:

I. Simm & Bertsimas' robust optimization model.

II. Scenario-Based robust optimization model (Malvey's approach).

3.1.2 | Simm & Bertsimas' robust optimization model

Converting a deterministic model into a robust optimization model using Simm & Bertsimas' method depends solely on the mathematical model's structure. This section first describes and proves the robust optimization structure for the problem before examining its linear formulation.

Thus, the final structure of the problem is as follows:

$$\text{Min } Z = \max_{i \in I}\{C_i\}, \tag{6}$$

s.t.

$$\text{For all } i \in I, j \in J, \quad D_{ij}\, T_j \leq AT_j\, N_{ij} + \max_{\left\{\substack{S: S \subseteq J, |S| \leq \Gamma \\ (j_t, t_t) \in \frac{J}{S}}\right\}} \left(\sum\nolimits_{i=1} \sum\nolimits_{j=1} \widehat{D}_{ij} - (\Gamma - \lfloor \Gamma \rfloor)\, \widehat{D}_{i_t j_t}\right), \tag{7}$$

$$\text{For all } i \in I, j \in J, \quad X_{ij} = \frac{D_{ij}\, T_j}{N_{ij}}, \tag{8}$$

$$\text{For all } i \in I, \quad C_i = \sum\nolimits_{j \in J} X_{ij}, \tag{9}$$

$$\text{For all } j \in J, \quad \sum\nolimits_{i \in I} N_{ij} \leq AW_j. \tag{10}$$

Since the expression $\max_{\left\{\substack{S: S \subseteq J, |S| \leq \Gamma \\ (j_t, t_t) \in \frac{J}{S}}\right\}} \left(\sum_{i=1} \sum_{j=1} \widehat{D}_{ij} - (\Gamma - \lfloor \Gamma \rfloor)\, \widehat{D}_{i_t j_t}\right)$ includes only the demand parameter, the presence of the max function does not alter the model's nature or introduce an unsolvable nonlinear structure. Therefore, *Eq. (7)* can be directly utilized to solve the problem in this research.

3.1.3 | Malvey's robust optimization model

The robust optimization approach introduced by Malvey enables decision-makers to manage the risk of inconsistency or service level deviations, offering a set of solutions that are less sensitive to data fluctuations across different scenarios. In this study, service demand is considered uncertain and is incorporated into the model using scenario-based robust optimization. Similar to the previously discussed robust optimization approach, the Malvey robust model is formulated as follows. First, the sets, parameters, and decision variables are introduced in the following tables, followed by the mathematical model and constraints.

Table 3. Sets and notations in Malvey's robust optimization model.

Sets and Notations		
I	Set of centers	$I = \{i \mid i = 1,2,3, \dots \lvert I \rvert\}$
J	Set of services available at the centers	$I = \{j \mid j = 1,2,3, \dots \lvert J \rvert\}$
Se	Set of scenarios	$Se = \{Se \mid Se = 1,2,3, \dots \lvert Se \rvert\}$

Table 4. Parameters of Malvey's robust optimization model.

Parameters	
D_{ijse}	Average number of requests for service j in the active center i under scenario se
T_j	Time required to perform service j
AW_j	Number of specialists available to perform service j
AT_j	Time of availability of specialists for service j

Table 5. Variables of Malvey's robust optimization model.

Decision Variables	
N_{ijse}	Number of human resources required to perform service j in active center i under scenario se
X_{ijse}	Average waiting time for customers to receive service j in center i under scenario se
C_{ise}	Average waiting time for customers to receive service j in center i under scenario se

$$\text{Min } Z_{se} = \max_{i \in I}\{C_{ise}\}, \tag{1}$$

s. t.

$$\text{For all } i \in I, j \in J, se \in Se, \quad D_{ijse}\, T_j \le AT_j\, N_{ij}, \tag{2}$$

$$\text{For all } i \in I, j \in J, se \in Se, \quad X_{ij} = \frac{D_{ijse}\, T_j}{N_{ij}}, \tag{3}$$

$$\text{For all } i \in I, \quad C_i = \sum_{j \in J} X_{ij}, \tag{4}$$

$$\text{For all } j \in J, \quad \sum_{i \in I} N_{ij} \le AW_j, \tag{5}$$

where $TC_{se} = \max_{i \in I}\{C_{ise}\}$,Therefore, according to the robust optimization structure explained, the robust model of the problem is as follows.

$$\text{Min } Z = \sum_h Pr_h\, TC_h + \lambda \sum_h Pr_h\, |TC_h - \sum_{h'} P_{h'}\, TC_{h'}| + \omega(\sum_h Pr_h\, \delta).$$

Subject to:

Other constraints

$$D_{ijse}\, T_j \le AT_j\, N_{ij} + \delta, \text{ For all } i \in I, j \in J, se \in Se,$$

$$X_{ij} = \frac{D_{ijse}\, T_j}{N_{ij}} - \delta, \text{ For all } i \in I, j \in J, se \in Se.$$

However, the above objective function is nonlinear due to the presence of absolute value, and the problem is converted into linear programming by introducing two new variables, p_h and q_h, as follows. The constraint $q_h - p_h = TC_h - \sum_{h'} Pr_{h'}\, TC_{h'}$ is added to the main model.

$$\text{Min } Z = \sum_h Pr_h\, TC_h + \lambda \sum_h Pr_h\, (q_{1h} + p_{1h}) + \omega \sum_s \sum_h P_s\, \delta_{hs},$$

s. t,

Other constraints

$$q_h - p_h = TC_h - \sum_{h'} Pr_{h'}\, TC_h.$$

Problem solving

In this example, three service centers offer customers four different types of services. The input data for this case study is provided in the following table.

Table 6. Input data for a small-scale numerical example.

Service 4 (Suspension)	Service 3 (Battery Repair)	Service 2 (Painting)	Service 1 (Bodywork)		
11	20	17	10	Center 1	D_{ij}
19	19	15	16	Center 2	
15	19	19	12	Center 3	
4 hours	1 hour	8 hours	2 hours	T_j	
8	15	8	12	AW_j	
8 hours	8 hours	8 hours	8 hours	AT_j	

Based on the above data, the graphical structure of the problem is represented as follows.

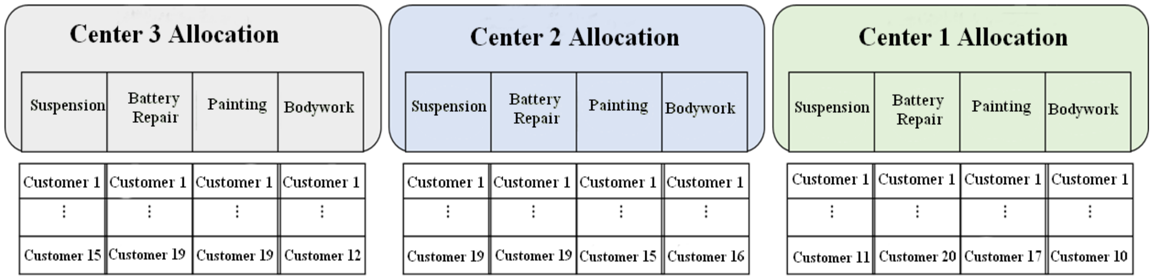

Fig. 1. Graphical representation of the problem.

As illustrated in *Fig. 1*, each customer must wait in line based on their initial position in the queue. A preliminary calculation reveals that the average customer waiting time is determined by dividing the total waiting time by the number of customers. For example, in service center 1, the waiting time for body repair services is calculated as 5.5 hours using the following formula:

$$\frac{\text{Waiting time for Customer 1 + Waiting time for Customer 2 + ... + Waiting time for Customer 10}}{\text{Total number of customers}} =$$

$$\frac{0+2+4+6+8+10+12+14+16+18+20}{10} = \frac{110}{10} = 11.$$

As observed, the average customer waiting time for service is 11 hours. Given the presence of 12 workers, the service delivery time per customer is 0.92 hours. Similar calculations can be performed for other services across all centers. The computational results are presented in the following table after solving the optimization problem using the CPLEX solver. As previously explained, the mathematical model attempts to reduce the maximum waiting time for customers at service centers to receive their desired services. However, this optimization is achieved by moving specialist personnel between centers, the problem's decision variable.

Table 7. Decision variable values obtained from CPLEX solution.

Service 4 (Suspension)	Service 3 (Battery Repair)	Service 2 (Painting)	Service 1 (Bodywork)		
3	4	2	2	Center 1	
2	6	1	3	Center 2	N_{ij}
7	1	1	1	Center 3	
0,15	0,0.5	0,68	0,10	Center 1	
0,38	0,0.3	1,20	0,11	Center 2	X_{ij}
0,0.9	0,19	1,52	0,24	Center 3	

Based on the computed variables, the maximum waiting time across all centers is 2.07 hours, which is exactly the objective function value of the problem. In fact, by reallocating specialized personnel among centers, customer's waiting time may be further reduced. In the initial state, the maximum customer waiting time was 3.12 hours, and the achieved improvement amounts to 1.05 hours (50.7% reduction). However, it is essential to recognize that the allocation problem belongs to the NP-hard class, meaning that metaheuristic algorithms must be used to solve large-scale instances. Therefore, several numerical examples in small, medium, and large scales have been generated, and their results are presented and compared. Before that, however, the scenario-based robust optimization model is examined. As observed, the solution time for the deterministic model is the lowest, whereas the solution time for the robust model is the highest. As previously stated, increasing the number of constraints significantly impacts solution time, leading to a considerable increase.

4 | Sensitivity Analysis

Sensitivity analysis is performed on the robustness parameters to examine the problem's behavior under varying scenario effects. This analysis considers different scenario probabilities, and the objective function values are reported.

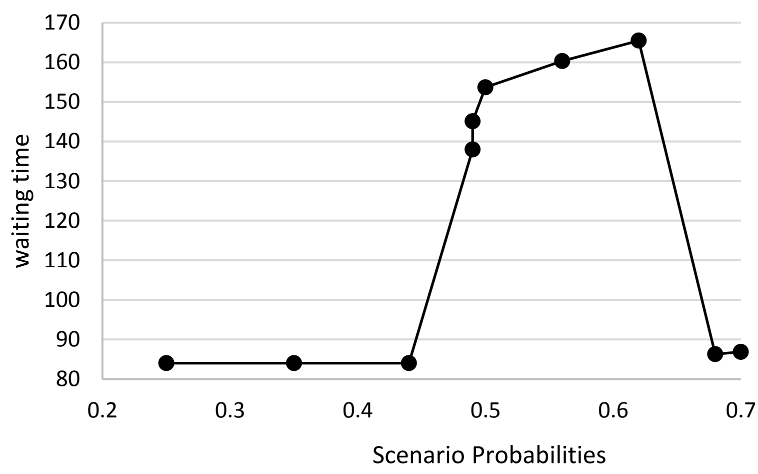

Fig. 2. System cost trend for different scenario probabilities.

The above graph depicts the system cost trend for various scenario probabilities. These changes occur only in the first scenario, where scenario 1 is set at the reported value, while Scenarios 2 and 3 follow a 1:2 ratio. For instance, if Scenario 1 is assigned a probability of 0.25, the remaining 0.75 probability is distributed as 1 share to Scenario 2 and 2 shares to Scenario 3, leading to Scenario 1 = 0.25, Scenario 2 = 0.5, and Scenario 3 = 0.25. According to the graph, initial task completion time is very low, but as scenario probability levels increase, customer's waiting time rises.

Moreover, several numerical examples were designed and analyzed to compare the model's performance with and without robust optimization. The following figure presents the obtained results.

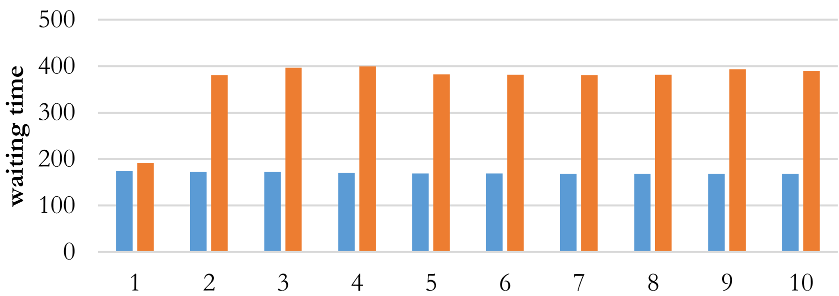

Fig. 3. Comparison of model performance with and without robust optimization.

In *Fig. 2*: The orange bars represent the system cost in the absence of robust optimization. The blue bars represent the system cost when robust optimization is applied.

As observed, system costs increase significantly without robust optimization. This rise is expected, as the lack of response-control variables causes the model's performance to deteriorate, leading to a significant deviation from globally optimal solutions.

5 | Comparison of Metaheuristic Algorithm Performance in Numerical Solution Generation

To assess the behavior of proposed algorithms in obtaining optimal solutions, the table below presents the results of solving various instances using the proposed metaheuristic algorithms. The parameter variation range is structured as follows:

Table 8. Results of solving various instances using the proposed algorithms.

D_{ij}	Uniform (50,60)	The average demand for service j at active center i
T_j	Uniform (1,7)	The time required to perform service j
AW_j	Uniform (1,10)	The number of specialists available to perform service j
AT_j	Uniform (8,40)	The available time of specialists for service j

It is noteworthy that 50 numerical instances were randomly generated for comparison. The numerical results are presented in the following table after solving the problem using the developed metaheuristic algorithms and the mathematical model. This table reports the objective function values and solution times for each computation. To standardize the numerical results, computations were evaluated based on the Relative Percentage Deviation (RPD) criterion, which is calculated as follows:

$$RPD = |\ \text{Alg sol} - \text{Best Sol}\ | * 100/\ |\text{Best Sol}\ |.$$

Table 9. Comparison of numerical results from different test instances.

	GAMS		Genetic			Harmony Search			Grey Wolf		
Row	Objective Function	Time	Objective Function	Time	Gap	Objective Function	Time	Gap	Objective Function	Time	Gap
1	0.778	333	0.778	23	0	0.778	13	0	0.778	14	0
2	0.95	445	0.95	33	0	0.95	13	0	0.95	16	0
3	0.923	686	0.923	38	0	0.923	24	0	0.923	20	0
4	0.795	774	0.795	43	0	0.795	28	0	0.795	43	0
5	0.971	994	0.92	70	0.052523	0.971	56	0	0.971	65	0
6	0.927	1035	0.859	73	0.073355	0.927	58	0	0.927	65	0
7	0.905	1538	0.891	79	0.01547	0.905	59	0	0.875	68	0.033149
8	0.885	1759	0.81	85	0.084746	0.885	74	0	0.842	72	0.048588
9	0.916	1763	0.84	118	0.082969	0.888	111	0.030568	0.901	79	0.016376
10	0.906	1950	0.843	124	0.069536	0.852	131	0.059603	0.831	79	0.082781
11	0.739	2208	0.692	131	0.063599	0.692	137	0.063599	0.674	83	0.087957
12	0.789	2363	0.714	132	0.095057	0.745	149	0.055767	0.766	102	0.029151
13	0.83	300<0	0.758	147	0.086747	0.815	156	0.018072	0.801	103	0.03494
14	0.952	300<0	0.908	169	0.046218	0.898	172	0.056723	0.88	106	0.07563
15	-	-	0.748	175	0.020942	0.745	198	0.024869	0.764	111	0
16	-	-	0.752	177	0.045685	0.788	201	0	0.77	112	0.022843
17	-	-	0.658	183	0.064011	0.678	214	0.035562	0.703	115	0
18	-	-	0.653	207	0.056358	0.692	214	0	0.682	131	0.014451
19	-	-	0.772	213	0.003871	0.775	228	0	0.765	138	0.012903
20	-	-	0.703	220	0.005658	0.707	240	0	0.706	156	0.001414
21	-	-	0.724	235	0.051114	0.763	252	0	0.717	164	0.060288
22	-	-	0.87	238	0	0.86	258	0.011494	0.811	182	0.067816
23	-	-	0.709	239	0.057181	0.744	262	0.010638	0.752	191	0
24	-	-	0.673	240	0.086839	0.737	267	0	0.695	191	0.056988
25	-	-	0.911	242	0.026709	0.936	268	0	0.897	198	0.041667
26	-	-	0.646	242	0.08628	0.707	274	0	0.644	200	0.089109
27	-	-	0.68	245	0.028571	0.67	275	0.042857	0.7	201	0
28	-	-	0.91	256	0	0.908	300	0.002198	0.894	204	0.017582
29	-	-	0.785	268	0	0.756	303	0.036943	0.762	215	0.029299
30	-	-	0.729	280	0.050781	0.747	305	0.027344	0.768	218	0
31	-	-	0.748	292	0	0.703	307	0.06016	0.709	218	0.052139
32	-	-	0.756	297	0	0.748	316	0.010582	0.696	221	0.079365
33	-	-	0.875	317	0.022346	0.856	317	0.043575	0.895	252	0
34	-	-	0.847	322	0	0.801	328	0.054309	0.815	273	0.03778
35	-	-	0.933	325	0.003205	0.936	344	0	0.91	281	0.027778
36	-	-	0.905	338	0.008762	0.913	345	0	0.901	296	0.013143
37	-	-	0.755	342	0.050314	0.795	347	0	0.792	298	0.003774
38	-	-	0.721	345	0.075641	0.748	347	0.041026	0.78	299	0
39	-	-	0.955	348	0	0.944	347	0.011518	0.947	311	0.008377
40	-	-	0.797	357	0	0.747	361	0.062735	0.77	313	0.033877
41	-	-	0.718	357	0.028417	0.739	362	0	0.704	338	0.047361
42	-	-	0.911	361	0.001096	0.873	369	0.042763	0.912	354	0
43	-	-	0.699	369	0.027816	0.719	392	0	0.68	369	0.054242
44	-	-	0.716	370	0.050398	0.754	392	0	0.751	371	0.003979
45	-	-	0.778	380	0	0.751	396	0.034704	0.774	375	0.005141
46	-	-	0.931	391	0.012725	0.933	399	0.010604	0.943	384	0
47	-	-	0.872	392	0.001145	0.851	403	0.0252	0.873	387	0
48	-	-	0.73	400	0.012179	0.711	404	0.037889	0.739	408	0
49	-	-	0.728	404	0.014885	0.739	412	0	0.69	413	0.066306
50	-	-	0.714	413	0.036437	0.718	417	0.031039	0.741	420	0

According to the results in *Table 9*, the GWO exhibits a lower computational gap than other algorithms. Meanwhile, the Genetic Algorithm (GA) and Harmony Search Algorithm (HSA) perform similarly. Regarding solution quality, the results obtained from different algorithms are highly comparable, making it difficult to rank the algorithms based solely on their output quality.

Overall, the GWO performs better than other algorithms. In fact, for solving large-scale problems, GWO appears to be the most suitable final solution method. However, the following graphs illustrate the convergence trends of the proposed algorithms in reaching the final solution.

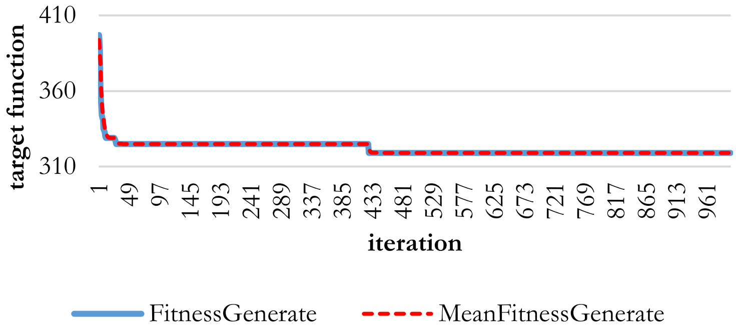

Fig. 4. Convergence of the HSA.

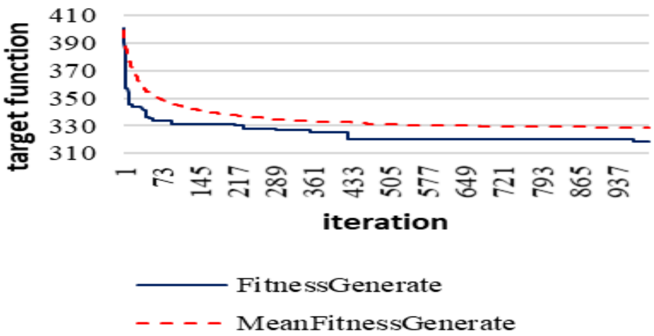

Fig. 5. Convergence of the GWO.

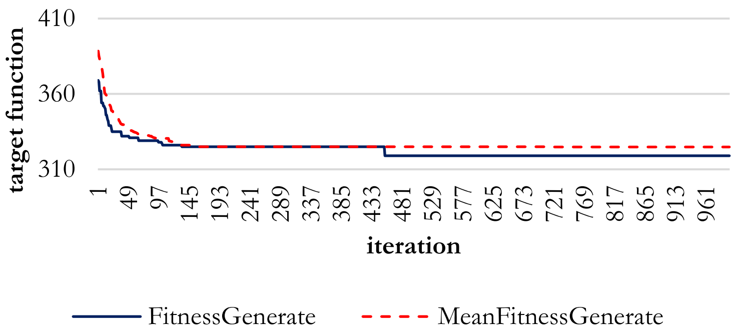

Fig. 6. Convergence of the GA.

A key observation is the difference between the best-found solution and the average solutions across iterations. Given the GWO's structure, which was discussed in the previous chapter, its powerful operators for generating new solutions lead to higher-quality results than other algorithms.

Large-scale examples were tested to analyze further algorithms' behavior in solving numerical instances, and defined performance metrics were used to compare the efficiency of different algorithms.

Table 10. Performance comparison of algorithms on large-scale numerical instances.

Genetic					Harmony Search				Grey Wolf			
Notation	Solution Time (seconds)	Final Answer (minutes)	Number of Iterations to Reach the Final Answer	Variance of Answers in the Final Answer	Solution Time (seconds)	Final Answer (minutes)	Number of Iterations to Reach the Final Answer	Variance of Answers in the Final Answer	Solution Time (seconds)	Final Answer (minutes)	Number of Iterations to Reach the Final Answer	Variance of Answers in the Final Answer
1	15.3	8318	488	9	9.3	7110	358	6	8.6	6130	468	6
2	15.6	9013	405	15	11.1	7704	388	7	10.8	6758	417	2
3	15.9	8064	393	11	10.8	7200	422	8	10.5	6429	300	2
4	12.8	10450	346	16	11.1	8709	345	8	8.0	7918	419	8
5	15.0	9389	485	11	10.9	8025	346	5	9.1	6744	394	1
6	12.5	9938	356	20	9.1	8352	454	4	10.8	7019	479	0.9
7	13.6	9493	395	12	10.8	8255	349	2	11.4	7179	350	2
8	14.9	9440	389	19	9.4	7867	383	4	11.6	6841	369	4
9	15.5	9581	480	10	10.6	8405	351	3	11.5	7184	452	0.9
10	14.4	10505	378	12	8.9	9464	307	1	10.6	7887	491	7
Mean	145/50	9419/10			102/00	8109/10			102/90	7008/90		
Variance	11/36	758/80			8/57	664/68			12/08	541/04		

As observed in the above Table, the solution time for the GWO and GA is significantly lower than that of the HSA. Furthermore, the variance of solutions in the final population differs significantly between these algorithms and HSA. In general, GWO and GA demonstrate superior efficiency compared to HSA, although GWO consistently outperforms in some instances, making it the most recommended algorithm in this study.

Case study analysis

Data analysis is a multi-step process involving summarizing, coding, and categorizing collected data from the sample population. This process aims to facilitate analyses and establish relationships between data to achieve the research objectives. This chapter systematically applies the proposed methodologies to analyze data, ensuring that research questions are effectively addressed.

Since the Imperialist Competitive Algorithm (ICA) demonstrated the best performance in solving numerical test cases, it was also selected to solve the case study problem. According to the study, 15 authorized Iran Khodro dealerships have been considered for customer allocation optimization. The geographical distribution of these dealerships is illustrated below.

Fig. 7. Geographical distribution of selected dealerships in this study.

Six different services are provided at each of these dealerships, with detailed service information presented in the following table.

Table 11. Dealership service information.

		Service 1 (Body Repair)	Service 2 (Painting)	Service 3 (Battery Service)	Service 4 (Suspension)	Service 5 (Electrical Repair)	Service 6 (Fiberglass Work)
	Center 1	158	62	37	32	76	145
	Center 2	153	62	49	37	73	147
	Center 3	104	79	53	47	79	112
	Center 4	107	74	65	39	71	122
	Center 5	122	79	33	37	60	146
	Center 6	195	56	62	38	71	102
	Center 7	166	62	57	42	90	181
D_{ij}	Center 8	156	55	38	35	68	172
	Center 9	163	75	44	41	79	137
	Center 10	186	54	36	33	60	198
	Center 11	135	71	45	36	88	192
	Center 12	142	66	70	47	68	171
	Center 13	116	71	68	45	71	144
	Center 14	117	56	33	31	79	190
	Center 15	106	68	37	43	62	164
	T_j	8 hours	10 hours	3 hours	4 hours	4 hours	8 hours
	AW_j	25	33	18	32	27	19
	AT_j	8 hours	8 hours	8 hours	8 hours	8 hours	8 hours

After solving the problem using the ICA, the convergence graph of the obtained solutions is illustrated below.

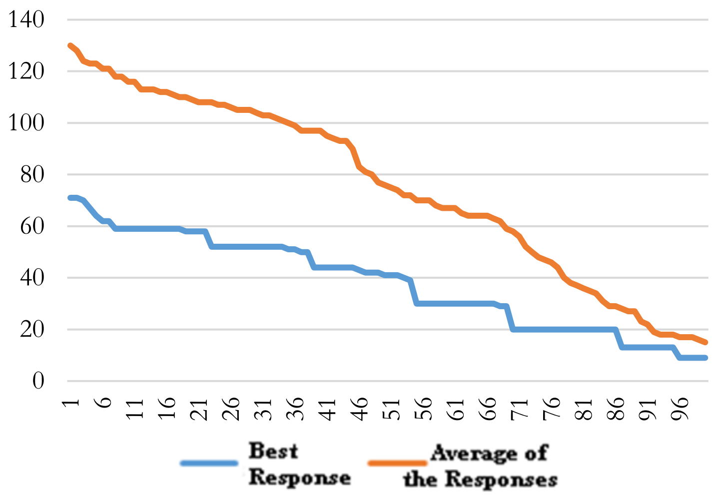

Fig. 8. Convergence of solutions in the case study.

As observed, the algorithm successfully generates highly similar solutions in the final iterations, indicating that the average solution is very close to the best-found solution. The maximum customer waiting time is set at 9 hours.

Table 12. Workforce allocation for each service at each center.

		Service 1 (Body Repair)	Service 2 (Painting)	Service 3 (Battery Service)	Service 4 (Suspension)	Service 5 (Electrical Repair)	Service 6 (Fiberglass Work)
	Center 1	2	2	1	4	1	1
	Center 2	1	1	1	1	2	1
	Center 3	2	4	1	2	3	1
	Center 4	2	2	2	1	1	1
	Center 5	2	1	1	4	3	1
	Center 6	2	4	1	3	1	1
	Center 7	2	2	1	1	1	1
D_{ij}	Center 8	1	2	1	2	2	3
	Center 9	1	2	1	2	2	1
	Center 10	1	4	1	4	2	1
	Center 11	1	1	2	1	1	1
	Center 12	2	1	2	2	3	1
	Center 13	2	2	1	1	1	1
	Center 14	1	3	1	3	1	1
	Center 15	3	2	1	1	3	3

According to the above Table, workforce allocation to each center for each service is illustrated.

Case study sensitivity analysis

This section conducted a sensitivity analysis of case study parameters to analyze further the algorithm's behavior in solving the research problem. Specifically, the number of service centers and service types was increased, and the objective function value was computed for each scenario.

Table 13. Sensitivity analysis results on case study parameters.

Number of Available Centers	Number of Services	Maximum Waiting Time of Customers
42	10	12
44	10	12
47	10	12
48	11	11.8
51	11	11.5
52	13	11.5
56	14	11.3
60	14	11.2
61	14	11.1
64	15	11
69	16	10.9
73	17	10.8
80	18	10.7
82	19	10.5
84	19	10.5
84	19	10.5
85	20	10.4
86	20	10
90	20	9.9
98	20	9.2

As observed, increasing the number of services and service centers reduces customers' waiting time. This is due to the balanced allocation of customers across multiple centers, which provides more options for customers and decreases overall waiting times.

5 | Conclusion

The present research developed a mathematical model for human resource management to minimize customer waiting times and enhance social satisfaction. While previous studies have focused on optimizing CRM, they have primarily relied on field studies and expert opinions, which can introduce errors. This study overcomes such limitations by designing a metaheuristic-based mathematical model without dependence on expert judgments. Questionnaires were used to identify customer needs, and customers were categorized based on the importance of cost, time, and quality. In addition, three metaheuristic algorithms–GA), HSA, and GWO–were developed to solve the problem. The GWO demonstrated the best performance.

The research initially validated the mathematical model using a numerical example, where multiple service centers were considered for fulfilling customer demands. The problem was solved using the CPLEX solver, and the obtained solution was feasible and well-optimized, confirming the model's efficiency. Since human resource allocation falls under NP-hard problems, three metaheuristic algorithms were employed to solve real-world scenarios. The numerical results consistently indicate that the GWO outperforms the other algorithms in nearly all instances. A key insight is that GWO's unique iteration structure leads to high-quality solutions, making it the most effective approach for large-scale workforce allocation problems.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Data Availability

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

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] Gazi, M. A. I., Al Mamun, A., Al Masud, A., Senathirajah, A. R. bin S., & Rahman, T. (2024). The relationship between CRM, knowledge management, organization commitment, customer profitability and customer loyalty in telecommunication industry: The mediating role of customer satisfaction and the moderating role of brand image. *Journal of open innovation: Technology, market, and complexity*, *10*(1), 100227. https://doi.org/10.1016/j.joitmc.2024.100227

[2] Malki, D., Bellahcene, M., Latreche, H., Terbeche, M., & Chroqui, R. (2024). How social CRM and customer satisfaction affect customer loyalty. *Spanish journal of marketing-esic*, *28*(4), 465–480. https://B2n.ir/nw1957l

[3] Khneyzer, C., Boustany, Z., & Dagher, J. (2024). AI-driven chatbots in CRM: Economic and managerial implications across industries. *Administrative sciences*, *14*(8), 182. https://doi.org/10.3390/admsci14080182

[4] Nwabekee, U. S., Abdul-Azeez, O. Y., Agu, E. E., & Ignatius, T. (2024). Digital transformation in marketing strategies: The role of data analytics and CRM tools. *International journal of frontline research in science and technology*, *3*(2), 55–72. https://doi.org/10.56355/ijfrst.2024.3.2.0047

[5] Iyelolu, T. V., Agu, E. E., Idemudia, C., & Ijomah, T. I. (2024). Improving customer engagement and crm for smes with ai driven solutions and future enhancements. *International journal of engineering research and development*, *20*(8), 1150–1168. https://B2n.ir/nm3529

[6] Durbiano, F., Pennecchi, F. R., Rolle, F., Pavarelli, S., & Sega, M. (2024). Stability study and uncertainty evaluation of CO2 certified reference materials for greenhouse gases monitoring. *Measurement*, *232*, 114653. https://doi.org/10.1016/j.measurement.2024.114653

[7] Liao, J., Zhan, Y., & Liu, K. (2025). Customer stability, environmental uncertainty and the cost of debt. *Discover journals, books & case studies*, *63*(5), 1787–1812. https://doi.org/10.1108/MD-07-2023-1268

[8] Shi, Y., Zhang, J., Ling, T., Lu, J., Zheng, Y., Yu, Q., Gao, Y. (2021). Inconsistency-aware uncertainty estimation for semi-supervised medical image segmentation. *IEEE transactions on medical imaging*, *41*(3), 608–620. https://doi.org/10.1109/TMI.2021.3117888

[9] De Oliveira, M. S., Steffen, V., de Francisco, A. C., & Trojan, F. (2023). Integrated data envelopment analysis, multi-criteria decision making, and cluster analysis methods: Trends and perspectives. *Decision analytics journal*, *8*, 100271. https://doi.org/10.1016/j.dajour.2023.100271

[10] Kheyri, S., Lotfi, F. H., Najafi, S. E., & Parchkolaei, B. R. (2022). Benchmarking automotive after-sales service companies with dependent criteria-application of data envelopment analysis. *International journal of industrial mathematics*, *14*(4), 401–413. http://dx.doi.org/10.30495/ijim.2022.62771.1543

[11] Wichapa, N., Pawaree, N., Nasawat, P., Chourwong, P., Sriburum, A., & Khanthirat, W. (2024). Process of solving multi-response optimization problems using a novel data envelopment analysis variant-Taguchi method. *International journal of technology*, *15*(6), 2038–2059. http://ijtech.eng.ui.ac.id/

[12] Dehghani, M., Montazeri, Z., Trojovská, E., & Trojovský, P. (2023). Coati optimization algorithm: A new bio-inspired metaheuristic algorithm for solving optimization problems. *Knowledge-based systems*, *259*, 110011. https://doi.org/10.1016/j.knosys.2022.110011

[13] Al-Baik, O., Alomari, S., Alssayed, O., Gochhait, S., Leonova, I., Dutta, U., Dehghani, M. (2024). Pufferfish optimization algorithm: A new bio-inspired metaheuristic algorithm for solving optimization problems. *Biomimetics*, *9*(2), 65. https://doi.org/10.3390/biomimetics9020065

[14] Hubálovská, M., Hubálovský, Š., & Trojovský, P. (2024). Botox optimization algorithm: A new human-based metaheuristic algorithm for solving optimization problems. *Biomimetics*, *9*(3), 137. https://doi.org/10.3390/biomimetics9030137

[15] Khosravi, A., Rajabzadeh, M., Zaloga, V., & Dyadyura, I. (2022). Customer knowledge management in enterprise software development companies: Organizational, human and technological perspective. *Management systems in production engineering*, (4 (30). https://doi.org/10.2478/mspe-2022-0037

[16] Jayasekera, T., Albattat, A., & Azam, F. (2023). The effects of customer orientation and technological capabilities on customer relationship management: The mediating effect of knowledge management. *Journal of law and sustainable development*, *11*(9), e1251--e1251. https://doi.org/10.55908/sdgs.v11i9.1251

[17] Chaithanapat, P., & Rakthin, S. (2021). Customer knowledge management in SMEs: Review and research agenda. *Knowledge and process management*, *28*(1), 71–89. https://doi.org/10.1002/kpm.1653

[18] Zia, U., Zhang, J., Xiaoyun, D., & Jinyan, L. (2024). Significance of knowledge management process and customer relationship management for stimulating innovation capability: Empirical analysis, PLS-SEM approach. *International journal of knowledge management studies*, *15*(1), 17–37. https://doi.org/10.1504/IJKMS.2024.138069

[19] Azzahra, N. A., & Hidayat, A. (2024). Analysis of the implementation of customer relationship management to increase customer loyalty and satisfaction at PT. Tunas Toyota Cilegon. *Finance: International journal of management finance*, *1*(4), 1–13. https://doi.org/10.62017/finance.v1i4.42

[20] Hu, L., & Basiglio, A. (2024). A multiple-case study on the adoption of customer relationship management and big data analytics in the automotive industry. *The tqm journal*, *36*(9), 1–21. https://doi.org/10.1108/TQM-05-2023-0137