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A MULTI-CHANNEL QUEUE MODEL TO OPTIMIZE SERVICE LEVEL AND STAFF AVAILABILITY IN BANK INDUSTRY

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Abstract. Staff scheduling in service organizations like banks, stores, call centers, and emergency centers is critical due to direct customer interaction and uncertain service demand. This research presents a multi-objective model for scheduling bank staff, focusing on uncertain customer arrival and service rates. The model aims to optimize customer service efficiency and maximize staff satisfaction through three objective functions: minimizing the customer waiting queue length (using an $M/M/C$ system), minimizing the number of assigned employees, and maximizing employee satisfaction by considering preferred working times. By simulating Poisson distribution for client arrival and service times, we predicted the bank's queue system performance and optimized staffing levels using the proposed model. Tested with real data from Agribank in Iran, the results showed an 8% reduction in customer waiting times and a 53% increase in employee satisfaction, demonstrating significant improvements in service efficiency and workplace morale. These percentages highlight the model's ability to effectively balance operational efficiency and employee well-being, facilitated by its transparent work pattern structure. Given the NP-hard nature of the model, we employed a meta-heuristic approach (NSGA-II) and GAMS with the ε-constraint method to solve it. Comparative results indicated that NSGA-II outperformed GAMS in both solution quality and computational time.

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1. Introduction

Staff scheduling is the process of determining work patterns (shift-day) according to the needs of the organization and its workforce, with the aim of minimizing costs, maximizing workforce satisfaction, and enhancing system performance [4]. Designing systems and processes to provide highly reliable services has become a key concern for leading organizations. Workforce performance is one of the main factors in developing such a system [34]. Staff scheduling is crucial in the service industry since the nature of service businesses (*e.g.*, healthcare, call centers, and banking) is dynamic, requiring schedules to adapt to changing customer demands [2]. Inefficient staff scheduling can result in long customer waiting times, lengthy queues, higher costs, and reduced productivity due to idle times. Conversely, efficient staff schedules can lead to optimal workforce utilization and increased customer satisfaction [23]. Managers face the challenge of balancing customer satisfaction by providing high

Keywords. Staff scheduling, optimization, employee satisfaction, queuing theory, NSGAII, bank industry.

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service levels while minimizing labor costs by scheduling as few employees as possible. The employee scheduling problem has attracted considerable research in the service industry due to the high costs associated with workforce utilization. Lee *et al.* [24] found that schedule flexibility significantly reduces turnover intent, as evidenced by their study of nine hotel properties in South Korea. Staff scheduling often involves complex combinatorial optimization problems, requiring efficient and effective approaches as traditional heuristic methods may not be sufficient [14].

Several researchers have focused on enhancing bank operations through staff scheduling. Mabert and McKenzie [28] outlined methods for scheduling shifts, forecasting workloads, and setting work priorities at Ohio National Bank, resulting in reduced float and increased profitability. Effective staff scheduling requires systematic planning, creativity, and accurate data. Optimizing employee work hours can boost motivation and productivity across various industries, including banking. In recent years, the banking industry has undergone significant changes, with customers now expecting more competitive and flexible services. Modern banks must efficiently utilize quality resources to meet these complex customer needs by offering quick, appropriate, and comfortable services [3]. Researchers have highlighted the need for effective methodologies to determine staffing levels given the high uncertainty in customer arrivals and service times. Ensuring the right employees are available at the right times is crucial for meeting customer demands and organizational needs.

Traditional research often focuses solely on reducing customer waiting times ($M/M/C$, multi-channel queue model) without considering employee preferences. This study addresses this gap by presenting a multi-objective model that considers both bank performance and employee preferences under uncertain conditions of customer arrival and service rates. The primary contribution of this paper is the development of a multi-objective optimization model incorporating three objectives: minimizing customer waiting times (using an $M/M/C$ queue model), minimizing the number of assigned employees, and maximizing employee satisfaction by considering their preferred working times. This model advances the literature on staff scheduling and optimization under uncertain conditions. Our literature review did not find studies addressing staff scheduling in the banking industry through the lens of queuing theory

In this paper, we examine staff scheduling for a real case in the banking industry to determine optimal shift schedules for employees. The model considers employee preferences, customer arrival rates, and employee seniority. We employ a genetic algorithm to solve this NP-hard problem. Our research extends the call center scheduling literature to banking, where employees must handle predefined tasks and assist at payment and receipt counters during peak times to enhance service speed and system efficiency. This paper is organized as follows: Section 2 reviews related research, Section 3 presents the problem statement and optimization formulation, Section 4 discusses solution approaches, Section 5 explains results and discussions, and Section 6 provides the conclusion.

2. Literature review

There has been extensive research in the field of employee scheduling, exploring various aspects of the scheduling problem. Recent papers that contribute to the development of this research field include Mansini *et al.* [29], Wang *et al.* [39] and Bahroun *et al.* [5]. Staff scheduling models that incorporate employee preferences and requests have evolved over time. Recent studies have developed models allowing employees to choose their shifts, rest hours, and preferred shift partners based on their experiences, seniorities, and priorities [5]. Research has shown that considering employees' requirements and requests in scheduling increases personnel satisfaction [33].

Idris [20] studied the effects of flexible work schedules on employee satisfaction and retention in the Malaysian banking industry. The findings indicated that the banking sector should implement more refined flexible work schedules to enhance employee retention, especially in developing countries. Ağralı *et al.* [2] examined staff scheduling in service sectors, accommodating fluctuating employee availability and demand. Their model aimed to mitigate service demand, enhance employee satisfaction, and ensure equitable workload distribution. Findings indicated the model's efficacy in fostering a conducive work atmosphere for both the organization and its adaptable workforce. Akbari *et al.* [4] aimed to maximize employee satisfaction by considering availability, seniority, and variable productivity. They introduced a Mixed-Integer Programming (MIP) model and solved it using meta-heuristics.

Easton [13] found that cross-training improves service levels and productivity by pooling demand streams, especially when negatively correlated. Using a two-stage stochastic model, he showed that increased scheduling flexibility reduces labor costs and enhances service levels in operations with uncertain demand and attendance. Effective staff scheduling in the service industry, aimed at reducing overstaffing and understaffing across multiple periods, is often hindered by a lack of flexibility resulting from the reliance on specialized personnel exclusively. To address this gap, Henao *et al.* [16] proposed a mixed integer linear programming model for determining employee training and assignments over a one-week period. The model demonstrated that the lowest total costs were achieved when personnel supply and demand were balanced. Liu [26] addressed a multi-skill, cross-utilization problem across various departments using a two-stage stochastic programming model to balance worker costs and meet demands. To minimize total worker costs, unmet demands were allowed with penalties. Factors such as worker cost coefficient, penalty factor, and worker efficiency were considered to optimize staffing levels. Dai and Li [11] addressed the staff scheduling problem in call centers with a focus on global service quality. Given that labor costs typically constitute approximately 70% of the total expenses, the authors incorporated a linear approximation function into their scheduling model. Their numerical analysis demonstrated that the new model accurately reflected real-world scenarios. Call centers encounter fluctuations in demand over time and often require cross-trained employees with flexible schedules to mitigate these variations. Taskiran and Zhang [38] developed an integer program to schedule shifts, days off, and breaks for cross-trained employees in call centers. Due to the complexity of their model, they devised a two-step sequential method for solving it. The first step involved determining the optimal mix of employees, followed by staff scheduling to establish the personnel composition and weekly schedules. Their experiments using data from a real call center underscored the effectiveness of their model in managing demand fluctuations. Mattia *et al.* [30] investigated staffing and scheduling challenges in flexible call centers. Unlike previous approaches, they considered uncertain staffing levels to ensure desired service quality. They proposed a two-step robust integer program with uncertainty in the right-hand side. The results demonstrated the efficacy of their approach in efficiently addressing real-world problems and providing enhanced protection against uncertainty. Zan *et al.* [40] studied staffing optimization in call centers under uncertain arrival rates using a Bayesian method. They formulated a two-stage optimization problem aimed at minimizing staffing costs while meeting service quality constraints during the second stage of operations.

Few scheduling optimization models have addressed the significant factor of uncertainty in employee scheduling within the service industry. To bridge this gap, Bürgy *et al.* [8] investigated employee scheduling in retail stores with short-term demand fluctuations and flexible shift extensions. These fluctuations led to increased demand during certain time intervals, prompting overtime assignments by extending shifts. The authors proposed two integer programming models with the objective of minimizing the sum of demand fulfillment and employee preference-related costs. Computational experiments conducted on real-world examples from retail stores demonstrated that the proposed models enhanced schedule quality by incorporating uncertainty information. Recognizing the importance of flexible worker schedules in mitigating over/understaffing and coping with unexpected demand variations, Porto *et al.* [35] explored the effects of a hybrid flexibility strategy on staff scheduling in retail service industries. Their study investigated the potential benefits of integrating workforce flexibility into staff scheduling, combining flexible employment contracts with multi-skilled staff capable of performing various tasks. They developed a mixed integer linear programming model to determine the optimal number of employees for different contract types and skills. Experiments conducted on real data revealed the potential advantages of the hybrid flexibility approach compared to scenarios where flexibility was not considered.

Due to the complexity of scheduling problems involving soft and hard constraints and uncertain parameters, many are classified as NP-hard. Kletzander and Musliu [21] tackled the general employee scheduling problem by developing a framework that encompassed a wide range of heuristic and meta-heuristic approaches. This framework allowed for the implementation of different heuristic algorithms across various employee scheduling problems, providing a comprehensive solution approach. Soriano *et al.* [37] addressed the limitations of existing employee scheduling models by considering varying employee demand per hour interval, diverse employee working conditions across disjoint shifts and breaks, and worker preferences. Their model, a combination of analytic hierarchy process and mixed integer linear programming, aimed to solve multi-dimensional problems and was capable of finding optimal and feasible solutions. In the context of service industries where prolonged waiting times incur increased costs, Hijry and Olawoyin [17] investigated the efficiency of a deep learning algorithm in predicting patient waiting times in queue systems. Although their method effectively predicted waiting times using real hospital data, it did not optimize system performance or consider employee considerations.

In contrast to existing approaches, leveraged a vast dataset of banking records to estimate labor banking time through modeling customer and bank services. Their study demonstrated the effectiveness of a graph-based learning approach in addressing anonymous client and sparse interaction issues. Abusair *et al.* [1] utilized a queue management system to regulate customer waiting times in healthcare vaccination systems, emphasizing the impact of queue wait times on client experience and resource utilization. Their simulated experiment showed an improvement in customer queue wait times. Baron *et al.* [6] demonstrated the applicability of machine learning in solving a general queuing theory problem. By considering Poisson arrivals and general service times in a single-server system, they predicted the stationary queue-length distribution. Their study addressed the challenge of studying the continuous distribution of service times. While their model is beneficial for optimizing service system performance, it does not address workforce preferences optimization.

Waiting lines are unavoidable in health facilities, necessitating careful consideration of queuing aspects during the design of healthcare facilities. Kuaban *et al.* [22] examined a finite capacity multi-server queuing model, highlighting its potential applications in managing patient impatience and capacity constraints. Miao *et al.* [31] developed an optimization model to maximize company profits by optimizing process configurations, component selections, and pricing, alongside determining the optimal number of servers to balance average waiting time and service costs. Their approach demonstrated higher profitability compared to traditional methods.

To retain clients during high demand periods, service providers may increase service rates [25]. Puha and Ward [36] proposed a fluid scheduling model for a multiclass many-server queue with impatient customers and variable arrival times. This model suggests using static priority scheduling to minimize long-run average abandonment rates and different policies when holding costs are involved. Ibrahim [19] focused on personalized scheduling policies using individual customer service time information, leveraging underlying stochastic process realizations beyond probability distributions. Zychlinski [41] developed a fluid deterministic model for the dynamics of queuing systems, emphasizing its application in service and healthcare operations management. Hu *et al.* [18] proposed a multiserver queuing model with moderate and urgent customer classes, optimizing scheduling by allowing customer class transitions while waiting. They prioritized service based on the urgency and potential proactive service for moderate customers. Zychlinski *et al.* [42] introduced a multiserver queuing model with multiple customer classes requiring different resource amounts, developing an index-based policy called the idle-avoid $c\mu/m$ rule to balance holding costs, service rates, resource requirements, and priority-induced idleness. Using queuing systems to minimize average queuing time is studied in various research fields, and it has been proven that the optimization algorithms provided are efficient [15, 27].

We have summarized some significant papers in the field of staff scheduling and optimization in Table 1.

The literature review reveals a recent trend in incorporating uncertainties into employee scheduling problems to address real-world challenges. Among service industries, the banking sector plays a pivotal role due to its direct interaction with customers. In today's competitive landscape, banks are expected to provide efficient services to remain competitive. Surprisingly, our survey did not uncover any studies addressing scheduling issues within the banking industry, particularly under uncertain conditions. Furthermore, our review of related literature found no papers addressing conflicting objectives related to system performance and employee satisfaction in optimization models. In this article, we aim to fill this gap by developing an employee scheduling optimization model with three objective functions, considering the uncertainty of customer arrival and service rates. Additionally, we propose an effective solution method for this NP-hard problem.

TABLE 1. Significant papers in staff scheduling and optimization.

Research	Key focus	Findings and contributions
Idris [20]	Flexible work schedule on employee retention in Malaysian banking industry	The bank industries should contribute to a more refined pattern of flexible work
Ağralı *et al.* [2]	Optimization in service industries considering service demand, employee satisfaction and fairness	The model generated an applicable and satisfactory work environment
Kyritsis and Deriaz [23]	Machine learning in bank industry in managing queues of different scenarios and industries	Machine learning is a viable alternative to queuing theory for predicting waiting time
Dai and Li [11]	Staff scheduling problem in call center	The new model was conformed to reality
Taskiran and Zhang [38]	Shift scheduling for cross-trained employee in call center	Find an optimal mix of employee and staff scheduling
Mattia *et al.* [30]	Flexible staffing and scheduling in call centers	Provided higher level of protection against uncertainty in staff level
Zan *et al.* [40]	Staffing in call centers with bayesian method	Minimized the staffing costs while satisfied a service quality constraint on the second stage operation under uncertain arrival rate
Bürgy *et al.*, [8]	Employee scheduling in retail stores	Enhanced the demand in some time intervals and assigned overtime work
Porto *et al.* [35]	Staff scheduling in service industry of retailing	Proposed flexibility strategy for contracts of employees and multi-skilled staff
Puha and Ward [36]	Fluid scheduling model with time-varying input for multiclass, many-server queues	Proposed static priority scheduling to minimize long-run average abandonment rates and different policies for scenarios involving holding costs.
Kletzander and Musliu [21]	Heuristic approach in scheduling	The implementation of different heuristic algorithms to a wide range of problems
Soriano *et al.* [37]	Decision making theory considering varying demand per hour interval, various employee working	Solve a multi-dimensional problem by combination of AHP and mixed integer linear programming
Hijry and Olawoyin [17]	Deep learning in hospital	The proposed model predict patients' waiting time with more accurate
Mo *et al.* [32]	Graph theory in bank industry	Providing a framework to learn representations of clients and services of banks and estimate the personal banking time
Baron *et al.* [6]	Machine learning regarding stationary queue-length distribution of an $M/G/1$ queue (Poisson arrivals, general service times, one server)	Empirically demonstrated the ability of machine to analyze a general queuing model
Kuaban *et al.* [22]	Multi-server queuing model with finite capacity	Addressed patient impatience and capacity constraints in healthcare settings
Miao *et al.* [31]	Optimization model for profit maximization and server scheduling	Demonstrated higher profitability compared to traditional methods by optimizing process configurations, component selections, pricing, and server numbers
Hu *et al.* [18]	Multiserver queuing model with moderate and urgent customer classes	Proposed optimal scheduling allowing transitions between customer classes and characterized priority rules for moderate and urgent customers
Lin *et al.* [25]	Service rate adjustment during high demand	Suggested increasing service rates to retain clients in the queue during high demand periods
Ibrahim [19]	Personalized scheduling policies using individual customer service time information	Leveraged individual realizations of stochastic processes for personalized scheduling, beyond using just probability distributions
Zychlinski [41]	Fluid deterministic model for queuing system dynamics	Focused on the application of fluid models in service and healthcare operations management
Zychlinski *et al.* [42]	Multiserver queuing model with multiple customer classes and resource requirements	Developed the idle-avoid cμ/m rule, an index-based policy to balance holding costs, service rates, resource requirements, and priority-induced idleness

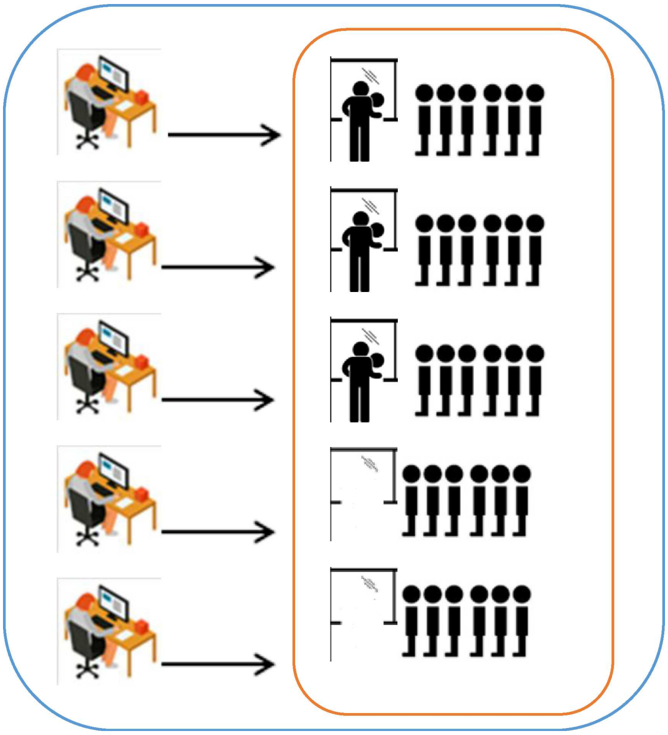

FIGURE 1. The problem scheme of assigning auxiliary staffs to the empty counters.

3. Problem statement and formulation

This research models the scheduling problem of bank employees as an integer programming problem. The study focuses on the staff and service system of Agricultural Bank in Mashhad. Service rate (μ) and customer arrival mean (λ) parameters are defined by simulating different distributions for customer arrival and service time. Visual SLAM is utilized to simulate the distributions. An optimization model, using queuing theory, models uncertain parameters related to variable demand for service. The waiting time variable represents the amount of time in minutes that each customer must wait in the queue before being served.

The objective functions of the proposed model are to maximize employee satisfaction and optimize customer service levels. Service level optimization aims to achieve the shortest customer waiting queue with the fewest employees. This study considers an $M/M/C$ bank queue system, which includes C service channels, each with an equal service rate (μ). The customer arrival rate is denoted by λ. In this context, there are n employees and C service channels per shift. Employees serve as auxiliary workforce; in addition to their predefined tasks, they are assigned to payment and receipt counters (service channels) during peak hours to expedite customer service and improve system efficiency. The time period is divided into eight one-hour intervals. Employees have different seniority levels, with each level assigned a weight reflecting their seniority. Consequently, employees with higher seniority levels have higher priority for assignment to their preferred time slots at the service channels. The problem definition is illustrated in Figure 1. For instance, on the left side of Figure 1, five employees are performing their predefined tasks. On the right side, there are three staffed cash counters and two unstaffed cash counters. These five employees must be allocated to the empty cash counters based on their availability and preferred time slots throughout the day to minimize the customer waiting queue.

For the mathematical modeling of staff scheduling, the relevant indices and parameters are defined as follows.

TABLE 2. Variables of the mathematical model and their descriptions.

Variables	Description
x_{itk}	Decision variable representing whether employee i is assigned to time t in working day k (1 if assigned, 0 otherwise)
c_{tk}	Decision variable representing whether the service channel is active at time t in working day k (1 if active, 0 otherwise)
L_q	Average number of customers in the queue

Indices

i Employee index $(i : 1, 2, \ldots, n)$
t Time interval index $(t : 1, 2, \ldots, 8)$
k Index of working days per week $(K : 1, 2, \ldots, 6)$

Parameters

λ_t Customer arrival rate to the bank in time t
μ Customer service rate
p_{it} Preferred time interval of employee i in time t. It is 1 if employee i prefer to be assigned to service channel in time interval t, and is 0 otherwise
l_i Maximum number of hours which employee i is allowed to be assigned in service channels each day. The amount of this parameter is based on employee's seniority which means more seniority equal to fewer allowed time intervals
C_k The maximum allowed service channel for day k
w_i The weight of employee i based on his/her seniority and is equal to the number of years of work experience for the employee

Decision variables

The variables used are explained in Table 2 as follows.

Assumptions

To develop our model, we considered some assumptions which are related to our case study and are as follow.

(1) For each day there are eight 1 h working time intervals.
(2) For each 1 h time interval we considered a customer entry rate.
(3) The service rate of the employees is equal to each other.
(4) Customers have the same service priority.
(5) Employees' preferences to assign working time interval are considered according to their seniority and experience.

To clarify the objective function, a notation table is provided in Table 3.

3.1. Mathematical formulation

Based on our notation and definitions we have developed our multi-objective optimization model as follows.

$$\text{Min } z1 : \text{Min } L_q = \sum_{k=1}^{6}\sum_{t=1}^{8}\left[\left(1 + \sum_{n=1}^{c_{tk}-1}\left(\frac{\lambda_t}{\mu}\right)^n\left(\frac{1}{n!}\right) + \left(\frac{\lambda_t}{\mu}\right)^{c_{tk}}\left(\frac{1}{c_{tk}!}\right)\sum_{n=c_{tk}}^{\infty}\left(\frac{\lambda_t}{c_{tk}\mu}\right)^{n-c_{tk}}\right)^{-1}\right]$$

TABLE 3. Optimization objective and their descriptions.

Objective function	Description
Equation (1)	Maximizes customer service level by minimizing L_q, which denotes the average number of customers in the queue
Equation (2)	Minimizes the allocation of supplementary workforces to service channels
Equation (3)	Aims to maximize employee satisfaction by minimizing the total deviation of assigned time intervals from employees' preferred times

$$\times\left[\left(\frac{\lambda_t}{\mu}\right)^{c_{tk}}\left(\frac{1}{c_{tk}!}\right)\sum_{n=c_{tk}}^{\infty}(n-c_{tk})\left(\frac{\lambda_t}{c_{tk}\mu}\right)^{n-c_{tk}}\right] \tag{1}$$

$$\text{Min } z2 : \sum_{i=1}^{n}\sum_{t=1}^{8} x_{itk} \tag{2}$$

$$\text{Min } z3 : \sum_{i=1}^{n}\sum_{t=1}^{8} |x_{itk} - p_{it}| \times w_i \tag{3}$$

Subjected to:

$$\sum_{i=1}^{n} x_{itk} = c_{tk} \qquad (i:1,2,\ldots,n),(t:1,2,\ldots,8),(K:1,2,\ldots,6) \tag{4}$$

$$\sum_{t=1}^{8} x_{itk} \leq l_{ik} \qquad (i:1,2,\ldots,n),(t:1,2,\ldots,8),(K:1,2,\ldots,6) \tag{5}$$

$$c_{tk} \leq C_k \qquad (t:1,2,\ldots,8),(K:1,2,\ldots,6). \tag{6}$$

To optimize the service level, three objective functions have been defined. Equation (1) maximizes the customer service level by minimizing L_q, which denotes the average number of customers in the queue. Objective function (2) minimizes the allocation of supplementary workforces to service channels. The third objective function, presented in equation (3), aims to maximize employee satisfaction by minimizing the total deviation of assigned time intervals from employees' preferred times. Equation (4) determines the number of active service channels at time interval t on day k based on the decision variable x_{itk}. Equation (5) ensures that the total allocated time intervals for each auxiliary workforce do not exceed the permitted time. In our case study, each auxiliary workforce is allotted a specific time for working in a counter section, and constraint (5) reflects this allocation. Constraint (6) limits the number of active service channels for each time slot to a maximum allowable value of C_k. Given the NP-hard nature of the problem, two approaches have been employed to solve the mathematical model: GAMS and the ε-constraint method. Additionally, a meta-heuristic approach has been utilized. The results obtained from the exact solution and the NSGAII are evaluated and compared after tuning the algorithm parameters.

3.2. Waiting time prediction

To forecast customer waiting times and arrival rates, we utilized a dataset sourced from an Agribank branch situated in the eastern region of Iran. This dataset encompasses records of queues formed and services provided at the Agribank branch over a one-month duration. In total, 8450 customer instances were documented, with each entry comprising information on the respective client's service duration, entry time, and waiting duration.

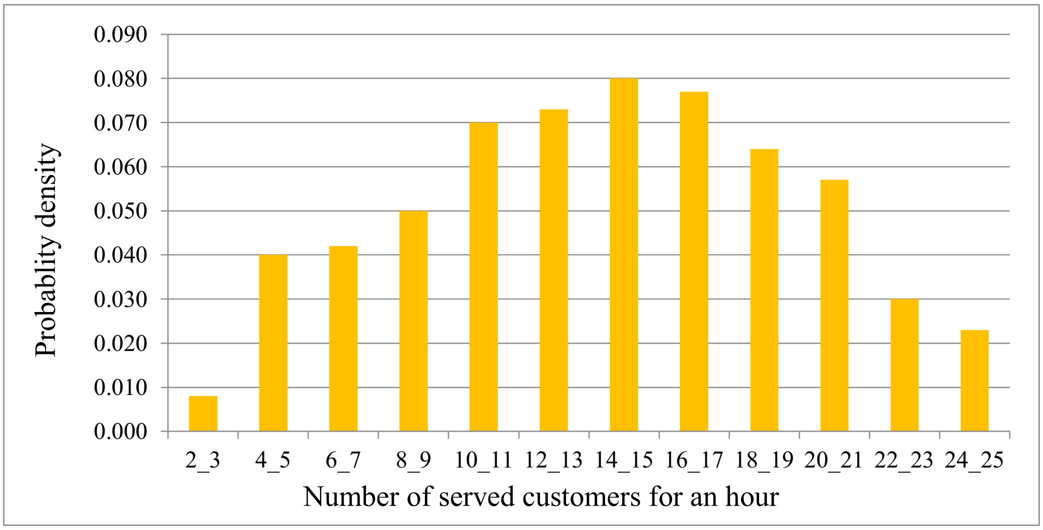

FIGURE 2. Histogram of service rate for one counter (a service channel).

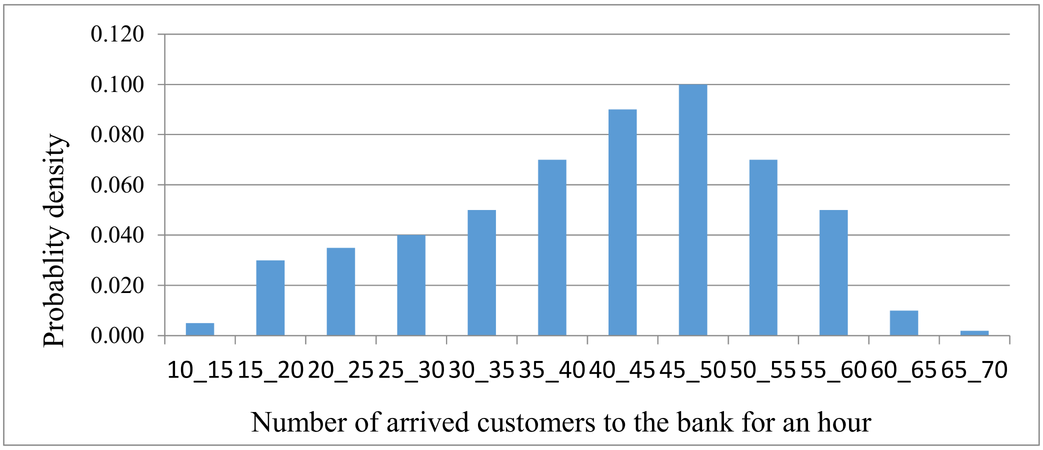

FIGURE 3. Histogram of arrival rate of customers.

Histograms illustrating the Poisson distribution of service rates and arrival rates for customers are depicted in Figures 2 and 3, respectively. It is pertinent to note that the dataset for Agribank's customers exhibits completeness, with no instances of missing data.

4. SOLUTION APPROACHES

4.1. GAMS and ε-constraint

To assess the accuracy and validity of the model, we utilized data from our case study focusing on small-scale instances. The model was solved using GAMS and the ε-constraint method, which yields Pareto-efficient optimal solutions suitable for such datasets. In the ε-constraint method, one objective function is designated as the primary objective for optimization, while the others are treated as constraints in the model. Furthermore, to

TABLE 4. The parameters of the problem in our case study of the Agribank.

Parameters	Time intervals							
	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$	$t = 8$
λ_t	60	60	65	70	75	60	60	60
μ	50	50	50	50	50	50	50	50
P_{it}	$P_1 = 1$ $P_2 = 1$ $P_3 = 1$ $P_4 = 0$ $P_5 = 0$	$P_1 = 1$ $P_2 = 0$ $P_3 = 1$ $P_4 = 0$ $P_5 = 0$	$P_1 = 1$ $P_2 = 1$ $P_3 = 0$ $P_4 = 1$ $P_5 = 0$	$P_1 = 1$ $P_2 = 1$ $P_3 = 0$ $P_4 = 1$ $P_5 = 1$	$P_1 = 1$ $P_2 = 0$ $P_3 = 1$ $P_4 = 1$ $P_5 = 1$	$P_1 = 1$ $P_2 = 0$ $P_3 = 1$ $P_4 = 0$ $P_5 = 1$	$P_1 = 0$ $P_2 = 1$ $P_3 = 0$ $P_4 = 0$ $P_5 = 1$	$P_1 = 0$ $P_2 = 1$ $P_3 = 1$ $P_4 = 0$ $P_5 = 0$

TABLE 5. The set Pareto of the provided problem.

ε	Objective function 1	Objective function 2	Objective function 3
1	4.25	8	9
2	4.25	8	9
3	4.25	9	10
4	4.25	10	16
5	4.25	12	20
6	4.25	14	22

TABLE 6. The optimum solution of the model using GAMS and ε-constraint method.

Employee	Time interval							
	1	2	3	4	5	6	7	8
1	✓	✓					✓	
2	✓		✓	✓				
3		✓			✓	✓		
4				✓	✓			
5							✓	✓

gauge the effectiveness of the proposed meta-heuristic algorithm, results from the exact method were compared against those from NSGAII.

For the assessment and validation of the mathematical model, we considered a scenario involving five bank employees over a six-day period, with each day comprising eight working hours. The input parameters for this scenario are detailed in Table 4. Within our model, two distinct seniority levels are defined: "expert" and "supervisor", with employees 1 to 3 categorized as experts and the remaining as supervisors. The maximum allowable hours for assignment to service channels (l_i) are set at 3 h for experts and 2 h for supervisors. Additionally, the value of C_k is set to 2 for this study. The weighting factors assigned to employees, based on their respective experiences, are as follows: $w_1 = 5$, $w_2 = 4$, $w_3 = 8$, $w_4 = 10$, and $w_5 = 12$.

The Pareto set for the problem obtained using GAMS and the ε-constraint method is presented in Table 5. Additionally, Table 6 showcases the optimal solution for a single day.

The evaluation of the results validates the solution's accuracy and feasibility, confirming adherence to the model's constraints. Notably, the activation of two service channels per time interval aligns precisely with

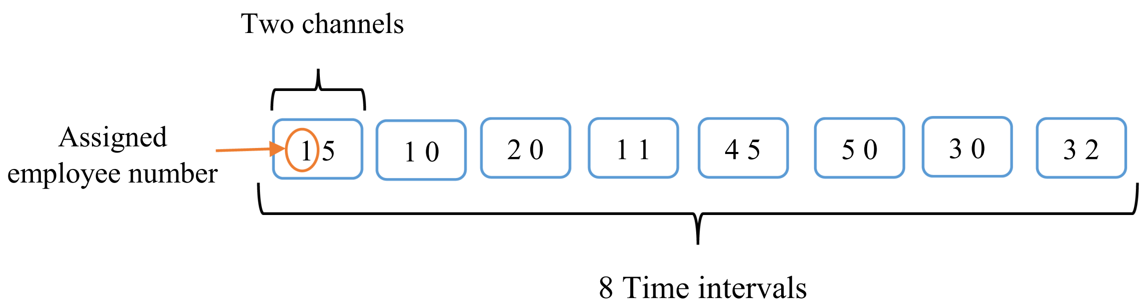

FIGURE 4. Chromosome representation.

the maximum permitted channels constraint. Analysis of the model's restrictions reveals full compliance with the limitations on the maximum number of assigned hours for both experts and supervisors. These findings underscore the efficacy of GAMS and the ε-constraint method in tackling the model, particularly for small-scale instances. Subsequently, we implemented the derived solution in our case study, leading to a notable reduction of up to 20% in the length of the customer waiting queue. Furthermore, the introduction of the new timetabling method significantly enhanced employee satisfaction, empowering them to select their preferred interval times for bank counter assignments. The positive feedback from bank staff regarding the clear work pattern structure bodes well for the bank's overall performance enhancement.

4.2. Multi-objective genetic algorithm

The staff scheduling problem is notoriously challenging to solve, even in simplified scenarios [9]. It is well-established that the scheduling problem is NP-complete [7]. Our model employs integer variables for workforce and service channel assignments, similar to previous research [9], and incorporates hard constraints that further complicate finding feasible solutions. In this study, the non-dominated sorting genetic algorithm II (NSGA-II) is utilized to address the multi-objective optimization problem. NSGA-II is one of the more effective algorithms for solving multi-objective optimization problems. It has been widely studied and proven to be robust and efficient in finding Pareto-optimal solutions [10]. To evaluate the efficacy of NSGA-II, its results are compared against those obtained from GAMS and the ε-constraint method. NSGA-II is renowned for its ability to converge to solutions at the optimal Pareto boundary in many cases [12]. The performance of evolutionary algorithms is heavily influenced by factors such as selection and crossover operators.

A concise description of the NSGA-II algorithm is outlined below:

(1) Initialization: Generate an initial population P_0 comprising N randomly selected solutions.
(2) Selection and Variation: Create an offspring population Q_t using binary tournament selection, crossover, and mutation operators applied to the parent population P_t. Combine the offspring population with the parent population to form the entire population R_t.
(3) Non-dominated Sorting: Apply a non-dominated sorting approach to population R_t to identify different non-dominated fronts for objective functions F_1, F_2, etc.
(4) Elitism: Create a new parent population $P_t + 1$ of size NN from the obtained non-dominated fronts F_i.
(5) Iteration: Repeat steps 2–4 until the maximum number of iterations is reached.

Solutions obtained from multi-objective optimization are typically represented as the Pareto front. No solution on the Pareto front dominates another, and each may be considered optimal depending on the context. Figure 4 illustrates the chromosome used to represent solvable solutions in the NSGA-II algorithm, designed for a problem involving 5 employees, 2 service channels, 8 time intervals, and 1 day.

The proposed chromosome is structured based on the number of time intervals, with each interval containing two genes representing the assignment of employees to channels. The value of each gene indicates which employee

TABLE 7. Different parameters of GA algorithm.

Parameters	The level
Population size	$70, 80, 90$
Crossover rate	$0.5, 0.6, 0.7$
Mutation rate	$0.10, 0.15, 0.18$
Maximum irritation	$70, 85, 100$

should be assigned to the respective channel. However, it is important to note that the chromosome may sometimes be infeasible. In such cases, we have introduced a notation to rectify the chromosome. Specifically, if the genes within a time interval are found to be equal, a random number between 0 and 8 is substituted to ensure diversity and feasibility.

Parameters tuning

To optimize the parameters using the Taguchi method, we conducted experiments with the parameters of initial population size, crossover rate, mutation rate, and maximum number of generations at three levels. The quality level of the solution was determined by averaging the obtained solutions, while computational time served as a measure of algorithm efficiency. The factors and levels of the genetic algorithm are detailed in Table 7, and the results of running NSGA-II with different factor levels are provided in Table 8.

We utilized the correlation coefficient of factors to determine the signal-to-noise ratios in the experimental design for the genetic algorithm. At a 95% confidence level, it was found that the factors of maximum iterations (85), crossover rate (0.6), and population size (80) had the most significant impact on solution quality. The optimized parameters of NSGA-II are summarized in Table 9.

We conducted experiments with various instances to analyze the convergence of NSGA-II, as depicted in Figure 5. Figure 5 illustrates the notable convergence rate of the algorithm with optimized parameters, demonstrating its rapid progression towards a stable condition within a few generations.

5. Results and discussion

5.1. Comparing the results of NSGAII and GAMS

To assess the competitiveness of our algorithms compared to the solution obtained from mathematical integer programming, we conducted a comparative analysis between NSGA-II and GAMS software. Various examples with different parameter levels were tested on a computer equipped with 4.00 GB RAM, a 2.34 GHz processor, and the Windows 8 operating system. MATLAB software was utilized to implement the NSGA-II method.

Each instance was executed 10 times, and the computational results for problems of varying dimensions were presented. Notably, for our NP-hard problem, the GAMS software encountered difficulties in solving models with larger dimensions, even after running for 1 h. We compared the solution quality and computational time between GAMS software and NSGA-II for the provided instances, as outlined in Table 10.

Table 10 reveals a performance comparison between the NSGA-II algorithm and GAMS software, indicating that the genetic algorithm outperforms GAMS in terms of both objective function value and computational time. This observation aligns with the anticipated superiority of meta-heuristic algorithms over mathematical integer programming methods in tackling complex optimization problems. In smaller instances, NSGA-II achieved objective function values comparable to those obtained by GAMS but within notably shorter computational times. This underscores NSGA-II's proficiency in efficiently converging towards near-global optimum solutions.

During our evaluations of GAMS performance, we noted instances where GAMS struggled to enhance initial solutions in smaller examples, despite prolonged running times. We attribute this behavior to the inherent

TABLE 8. The results of running the NSGA-II with different factors levels.

Population size	Crossover rate	Mutation rate	Maximum irritation	Solution	CPU time (s)
70	0.50	0.18	70	4.89	9.46
70	0.50	0.18	85	4.89	9.88
70	0.50	0.18	100	4.89	12.32
70	0.60	0.10	70	4.25	9.77
70	0.60	0.10	85	4.25	10.41
70	0.60	0.10	100	4.25	15.32
70	0.70	0.15	70	4.25	10.38
70	0.70	0.15	85	4.25	10.02
70	0.70	0.15	100	4.25	9.65
80	0.50	0.10	70	3.87	11.06
80	0.50	0.10	85	3.65	12.11
80	0.50	0.10	100	3.65	13.41
80	0.60	0.15	70	3.87	11.86
80	0.60	0.15	85	3.87	12.68
80	0.60	0.15	100	3.65	13.65
80	0.70	0.18	70	4.02	12.01
80	0.70	0.18	85	3.87	13.49
80	0.70	0.18	100	4.25	17.11
90	0.50	0.15	70	4.02	12.98
90	0.50	0.15	85	4.02	11.84
90	0.50	0.15	100	3.87	13.64
90	0.60	0.18	70	3.87	13.01
90	0.60	0.18	85	3.65	15.49
90	0.60	0.18	100	3.87	13.18
90	0.70	0.10	70	3.65	13.36
90	0.70	0.10	85	3.65	15.62
90	0.70	0.10	100	3.65	14.51

TABLE 9. The values of tuned parameters of NSGA-II.

Parameters	Level
Population size	80
Crossover rate	0.60
Mutation rate	0.15
Maximum irritation	85

characteristics of NP-hard problems, typified by numerous local optima and presenting formidable challenges for conventional optimization methodologies.

5.2. The effect of uncertainty in the results

To investigate the impact of considering uncertainty on optimizing the bank's service level, we conducted a comparative analysis between the output of our optimization model and the actual performance observed at the bank. This analysis utilized one month's worth of data encompassing customer waiting times, arrival rates, service rates, and the number of active bank counters. By applying this real-world data to solve the optimization problem, we aimed to assess the efficacy of our model in practical settings.

Table 10. The results of GAMS and NSGAII for different problems.

Instances	Size of the problem	Working days	Time intervals	Number of employees	Service channels	GAMS solution	Computational time (second) of GAMS	NSGAII solution	Computational time (second) of NSGAII
1	Small	3	2	2	2	5.24	36.00	5.24	9.26
2	Small	3	4	4	2	5.64	38.45	5.64	9.62
3	Small	4	4	4	2	5.17	42.00	5.17	8.45
4	Small	4	4	4	2	5.64	41.50	5.64	8.78
5	Small	4	4	4	2	5.11	1540.00	5.11	9.64
6	Small	5	4	4	3	5.62	1500.00	5.62	8.19
7	Medium	10	5	4	3	7.16	3520.00	3.55	9.81
8	Medium	10	5	4	3	7.28	3600.00	3.10	11.47
9	Large	20	5	4	3	No solution	–	13.64	10.43
10	Large	20	5	4	3	No solution	–	14.41	12.37
11	Large	25	5	4	3	No solution	–	15.37	13.41
12	Large	25	5	4	4	No solution	–	16.47	14.21
13	Large	25	6	5	4	No solution	–	16.34	13.49
14	Large	30	6	5	4	No solution	–	21.13	16.64
15	Large	30	6	5	4	No solution	–	20.81	14.13
16	Large	30	6	6	4	No solution	–	19.64	14.74
17	Large	30	7	6	4	No solution	–	22.72	15.84
18	Large	40	7	6	5	No solution	–	24.13	15.31
19	Large	40	7	7	5	No solution	–	23.15	14.36
20	Large	45	7	7	5	No solution	–	25.24	17.41
21	Large	45	7	7	5	No solution	–	26.12	21.41
22	Large	45	8	8	6	No solution	–	24.89	15.46
23	Large	45	8	8	6	No solution	–	24.41	13.64
24	Large	45	8	9	6	No solution	–	25.14	14.64
25	Large	50	9	9	6	No solution	–	27.61	13.49
26	Large	50	9	10	7	No solution	–	24.78	18.54
27	Large	50	9	10	7	No solution	–	25.15	16.79
28	Large	50	10	10	7	No solution	–	26.45	17.79
29	Large	50	10	10	7	No solution	–	28.78	18.84
30	Large	50	10	10	7	No solution	–	30.11	16.94

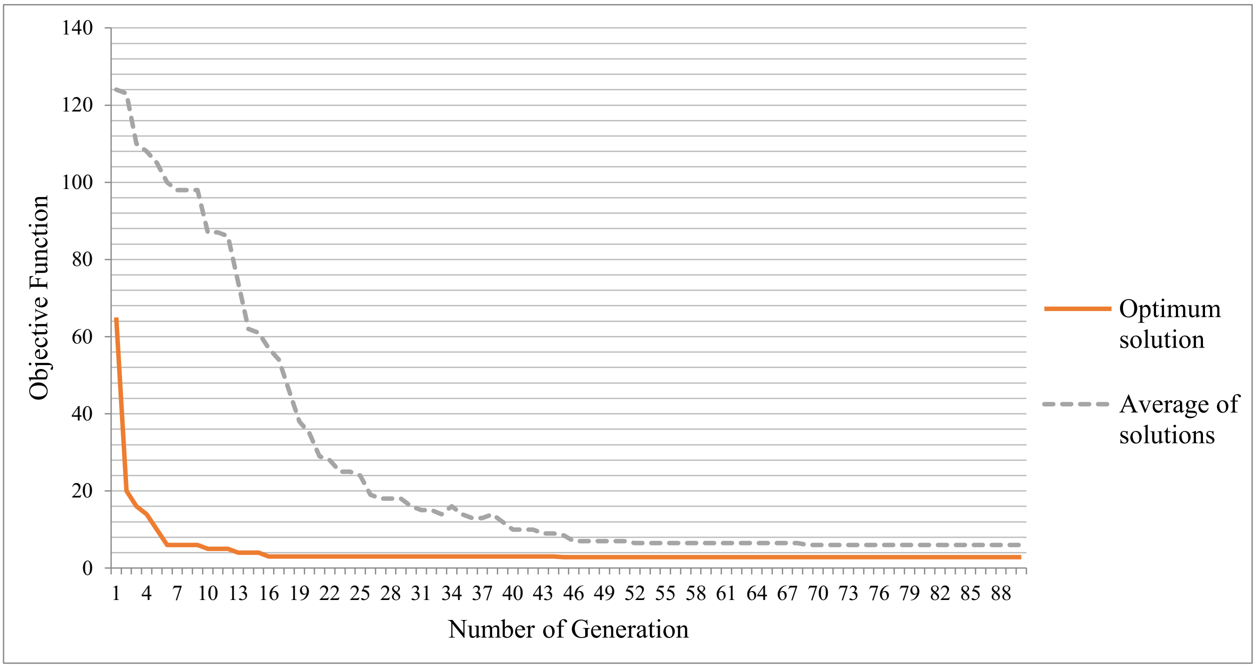

Figure 5. The convergence of NSGAII with tuned parameters.

Our experiments were conducted over an 8 h working period, with detailed results presented in Table 11. This rigorous examination allowed us to draw insightful conclusions regarding the effectiveness of our optimization approach in addressing the dynamic challenges inherent in banking service operations.

Comparing the solutions of the optimal model with the real scenario of the bank's customer service reveals compelling insights. For a typical working day, the average number of customers in the queue is lower in the optimal model solution (18.31) compared to the real scenario at the bank (19.92). This disparity indicates that the optimal model, accounting for uncertainties, provides a superior level of customer service. Furthermore, the optimal model allocates fewer working hours (17 h) compared to the real scenario (24 h) to minimize the average number of customers in the queue.

In addressing the third objective function, which aims to optimize employee satisfaction by ensuring fairness in the distribution of extra working hours, the results also demonstrate that employee satisfaction is higher in the solution generated by the mathematical model (10.55) compared to the real scenario (22.71). These findings underscore the effectiveness of the presented optimization model in enhancing customer service and employee satisfaction by considering uncertainties in customer arrival rates and service durations. Consequently, customer waiting times are reduced, employee satisfaction is increased, and surplus labor is minimized to achieve an optimal service level. Moreover, the comparison between the optimization model and the bank's real schedule indicates notable improvements. The optimal timetable has successfully reduced the length of customer queues by 8%, decreased the number of surplus employees by 29%, and increased employee satisfaction by 53%. These findings highlight the tangible benefits of employing the optimization model to streamline bank operations and enhance overall service quality while efficiently managing resources.

6. Research limitations and future directions

While this study provides valuable insights into staffing optimization modeling for banks, it's crucial to acknowledge its limitations. The research predominantly focused on a single case study at Agribank in Iran,

TABLE 11. The comparison of the optimization model with real scenario of Agribank.

Working hours of the bank	Objective 1: Average number of customers in the queue		Objective 2: The number of supplementary workforces		Objective 3: Employee satisfaction	
	Optimization model with uncertainties	The real situation without uncertainty	Optimization model with uncertainties	The real situation without uncertainty	Optimization model with uncertainties	The real situation without uncertainty
Work hour 1	0.23	0.00	1	3	0.31	2.14
Work hour 2	0.40	0.01	1	3	0.42	2.53
Work hour 3	3.21	3.10	2	3	1.50	3.38
Work hour 4	4.31	5.77	4	3	1.34	2.53
Work hour 5	4.12	5.56	4	3	2.12	3.46
Work hour 6	3.42	3.23	2	3	2.45	3.35
Work hour 7	2.41	2.20	2	3	1.36	2.56
Work hour 8	0.21	0.05	1	3	1.05	2.76
One working day	18.31	19.92	17	24	10.55	22.71
Percent of improvement	The percentage of improvement of the objective function 1 using the optimization model is **%8**		The percentage of improvement of the objective function 2 using the optimization model is **%29**		The percentage of improvement of the objective function 3 using the optimization model is **%53**	

potentially limiting the generalizability of findings to other banking institutions or service industries in varied contexts. To address this constraint, future research could adopt a multi-case or comparative case study approach, integrating data from multiple banks or financial institutions across diverse regions or countries. This would enable a more comprehensive analysis of the proposed staffing optimization model's effectiveness and applicability. Additionally, the study's reliance on Poisson probability distribution simulations to address uncertainties in customer arrivals and service times may oversimplify real-world banking operations' dynamic nature. To mitigate this, future research can explore advanced simulation techniques or hybrid modeling approaches, such as machine learning algorithms or agent-based modeling, to accurately capture real-world operational dynamics and customer behavior. Furthermore, investigating the long-term effects of the implemented staffing optimization model on bank efficiency, customer satisfaction, and employee morale would offer a more robust assessment of its impact. Conducting longitudinal studies or follow-up evaluations can track implementation outcomes over time, monitoring key performance indicators like customer satisfaction scores, employee turnover rates, and operational efficiency metrics to evaluate sustained benefits and identify areas for improvement. Involving key stakeholders, including bank managers, frontline staff, and customers, in the development and validation of the staffing optimization model ensures alignment with real-world needs and priorities. This engagement fosters buy-in and facilitates model implementation. Moreover, conducting sensitivity analyses to assess the model's robustness to input variations enhances the reliability and validity of findings, guiding decision-making under uncertainty by identifying critical influencing factors.

7. Societal implications

The proposed study on staffing optimization modeling for banks holds significant potential for societal benefit. By developing effective strategies for staff scheduling and resource allocation, the research aims to enhance the efficiency and quality of banking services, ultimately leading to improved customer satisfaction and experience. By reducing customer waiting times and streamlining service delivery processes, the proposed model can contribute to greater accessibility and inclusivity in banking, particularly for underserved communities or individuals with limited access to financial services. Moreover, by optimizing staff workload and improving employee satisfaction through flexible scheduling approaches, the research seeks to promote a healthier and more supportive work environment within banking institutions. This, in turn, can lead to increased employee retention, productivity, and well-being, contributing to overall societal welfare. Additionally, the findings from this study can inform policymakers and industry stakeholders in developing evidence-based strategies for enhancing operational efficiency and service quality in the banking sector, thus fostering economic growth and stability at both local and national levels.

8. Conclusion

In summary, this study successfully integrated queuing theory into staffing optimization modeling for banks, effectively addressing uncertainties in customer arrivals and service times through simulation of Poisson probability distribution. By developing an integer mathematical model for staff scheduling and applying it to a real case study at Agribank in Iran, we demonstrated significant improvements in bank efficiency and customer service levels. Our primary focus on optimizing surplus staff hours led to the development of a flexible scheduling model based on employee preferences, resulting in minimized customer waiting times and enhanced customer service efficiency.

Our implementation of multi-objective optimization using GAMS software and the ε-constraint method yielded Pareto efficient solutions, showcasing the efficacy of our model in reducing customer waiting queue lengths and ensuring employee satisfaction with the proposed scheduling. Furthermore, employing the NSGA-II algorithm for larger-scale problems underscored the effectiveness of our meta-heuristic approach in finding near-optimal solutions within reasonable computational time. The optimal timetable has successfully reduced the length of customer queues by 8%, decreased the number of surplus employees by 29%, and increased employee satisfaction by 53%. These findings highlight the tangible benefits of employing the optimization model to streamline bank operations and enhance overall service quality while efficiently managing resources.

For future research, we recommend exploring the integration of emerging technologies such as artificial intelligence, machine learning, and predictive analytics to further enhance the accuracy and efficiency of staffing optimization models in the banking sector. Furthermore, conducting robustness and sensitivity analyses to assess the stability and reliability of the proposed model under different scenarios and parameter variations could provide valuable insights for refining the model and improving decision-making processes in practice.

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