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Multi-Objective Shift Scheduling Optimization for Gas Pressure Reduction Stations: A Crow Search Algorithm and Gray Wolf Optimizer Approach

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Abstract. This study presents a multi-objective mixed-integer linear programming (MILP) model for optimizing rotational shift scheduling of personnel at gas pressure reduction stations (CGSs) and administrative offices of the Gas Company of Qom Province, Iran. The model simultaneously addresses organizational requirements and human-centric factors, including employee shift preferences, coworker compatibility, sensitivity to mercaptan gas, public communication skills, commuting distances, and regulatory workload constraints. A two-phase solution framework is employed: the multi-objective problem is first scalarized using the ε-constraint method, and the resulting single-objective subproblems are then solved using the Gray Wolf Optimizer (GWO) and the Crow Search Algorithm (CSA). An MILP-solver-based ε-constraint baseline is also reported for benchmarking. A real-world case study involving 49 employees, 9 service locations, and a 30-day planning horizon is used to evaluate the framework. Results from 30 independent runs show that CSA obtains lower average overtime (44.2 h versus 48.6 h), higher shift-preference satisfaction (90.1% versus 87.3%), higher coworker-preference satisfaction (86.4% versus 83.6%), and shorter average runtime (109.8 s versus 121.4 s) than GWO. Wilcoxon signed-rank tests indicate statistically significant differences at the 5% level. Sensitivity analysis reveals the trade-off between individual shift preferences and coworker compatibility under alternative weight settings. The framework therefore provides a practical and adaptable decision-support approach for workforce planning in continuous and safety-critical gas distribution operations.

Keywords. Personnel scheduling, Gas pressure reduction station, Multi-objective optimization, Crow search algorithm, Gray wolf optimizer.

MSC. 90B35; 90C11; 90C29.

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1 Introduction

Shift and personnel scheduling assign employees to work periods while satisfying coverage, labor-law, rest, skill, and organizational requirements. Well-designed rosters can reduce labor cost and service disruption while improving employee satisfaction, equity, and schedule acceptability [3, 11, 35]. The Personnel Scheduling Problem (PSP) encompasses shift scheduling, days-off scheduling, and tour scheduling, and its combinatorial structure becomes especially challenging when preferences, travel, qualifications, and fairness are represented simultaneously [3, 11].

Traditional PSP formulations frequently assume deterministic staffing demand and emphasize labor-cost minimization. Real applications, however, require a broader treatment of employee preferences, workload limits, and uncertain or variable operating conditions [34]. Integrated formulations may also include travel or routing decisions, which enlarge the solution space and make exact optimization difficult for operationally sized instances. Consequently, metaheuristic and hybrid optimization methods are often used to obtain high-quality feasible schedules within acceptable computation times [1, 17, 41, 44].

Efficient scheduling is particularly important in service organizations. Unlike manufacturing environments, where standardized shifts and fixed holidays are more common, service operations often experience daily and weekly variation in demand. Poor schedules can create overstaffing, understaffing, fatigue, avoidable overtime, and customer dissatisfaction [4, 42]. Recent scheduling studies increasingly incorporate human-centered objectives such as preferences, work-life balance, compatibility, fairness, and fatigue risk [28, 5, 39, 13].

Natural gas remains a major component of global energy supply, and Iran is among the countries with substantial natural-gas production and consumption [10]. In continuous energy operations, workforce availability and reliable shift coverage are essential because interruptions can affect safety, maintenance responsiveness, and service continuity. Previous work in natural-gas power plants has shown the value of formal personnel scheduling and competency-aware allocation [29, 30].

Gas pressure reduction stations (CGSs) reduce transmission pressure before gas enters local distribution networks. They require continuous monitoring and maintenance by qualified personnel, while associated administrative offices must provide uninterrupted customer-facing services. Existing CGS research has mainly addressed technical risk, resilience, inspection, and operational uncertainty [14, 22, 37, 43]. The human-resource dimension—particularly multi-objective rotational scheduling of technical and administrative personnel—has received far less attention.

This study develops a multi-objective MILP decision-support model for the Gas Company of Qom Province. Its main contribution is the joint treatment of shift preferences, coworker compatibility, mercaptan sensitivity, communication skills, commuting distance, staffing demand, rest rules, and overtime in one operational model. The ε-constraint method is used to structure trade-offs, while GWO and CSA are adapted to solve large instances. The contribution is evaluated on a real case with 49 employees, nine locations, and a 30-day horizon.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on personnel scheduling, metaheuristic optimization, and workforce planning in energy and service operations. Section 3 presents the multi-objective mathematical model, including notation, objective functions, and hard operational constraints. Section 4 describes the real-world case study of the Gas Company of Qom Province and details the data collection procedure and solution methodology. Section 5 reports the computational results, including statistical comparisons, workload and commute fairness analysis, and sensitivity analysis of the preference weights. Finally, Section 6 presents the conclusions and directions for future research.

2 Literature Review

Staff rostering has been studied extensively in healthcare, transportation, construction, audit, manufacturing, and public-service settings. Foundational reviews describe it as the allocation of limited human resources over time while satisfying demand, contractual rules, and quality criteria [11]. Healthcare applications have considered flexible blood-center staffing [16], home-healthcare routing and scheduling [7], preference-aware nurse rosters under attendance uncertainty [31], absenteeism and reactive rescheduling [28], clinic nurse-doctor pairing and individual preferences [39], and data-driven metaheuristic search [44]. Recent empirical work also emphasizes fatigue, participation, autonomy, and transparency in roster design [5, 33].

Recent optimization research demonstrates a shift toward integrated, human-centered, and computationally scalable models. Discrete GWO has been applied directly to nurse rostering [25], while hybrid and learning-assisted metaheuristics have been developed for complex nurse-roster instances [39, 44]. Flexible-time employee scheduling [17], shift-based integrated rostering and task assignment [41], and personalized hospital staffing [13] further show the importance of preferences, fairness, skills, and realistic labor rules. These studies support the use of population-based and hybrid methods when exact methods encounter scalability limits.

Fuzzy and preference-aware scheduling remain relevant because linguistic judgments cannot always be represented precisely. Pahlevanzadeh et al. [31] used Z-numbers to represent attendance assurance and uncertain nurse preferences. More recent work has applied fuzzy goal programming to nurse labor scheduling [20] and genetic fuzzy systems to part-time workforce scheduling [26]. In the present study, linguistic ratings are converted to crisp values by centroid defuzzification; this simplifies implementation but also motivates the uncertainty-related limitation stated in Section 6.

The ε-constraint method is a well-established scalarization approach for multi-objective optimization [9]. Effective implementations improve Pareto exploration by selecting one primary objective and converting the remaining objectives into bounded constraints [21]. In workforce and scheduling applications, Pareto-based formulations have been used to balance cost, preferences, coverage, and fairness [39, 41, 6]. Fairness can be assessed with inequality indicators such as the Gini coefficient; related scheduling and dispatch studies show how Gini-based measures quantify unequal allocation and the trade-off between fairness and schedule attractiveness [38, 6].

The methodology of this paper is related to Mohtadi et al. [24], which also compared CSA and GWO within a multi-objective allocation-and-scheduling setting. The present study introduces a different decision structure and operational domain: continuous two-shift gas operations, nine geographically dispersed CGS/office locations, employee-station-day-shift assignment variables, pairwise coworker compatibility, hazardous mercaptan exposure restrictions, public-communication skill matching, commuting distance, mandatory inter-shift rest, rolling workload limits, and overtime accounting. It also provides MILP-size analysis, a feasibility-repair operator tailored to gas operations, repeated-run statistical comparison, workload/commute fairness analysis, and sensitivity analysis of preference weights. These features delineate the methodological and managerial novelty relative to the war-tourism allocation problem in [24].

To assess the domain-specific research gap, a structured search was conducted using combinations of the terms "gas pressure reduction station," "compressor station," "personnel scheduling," "staff rostering," "shift scheduling," "maintenance workforce," "multi-objective," "GWO," "CSA," "fuzzy preference," and "ε-constraint" in major scholarly databases, with emphasis on publications through 2025. Retrieved CGS studies mainly addressed risk-based inspection, hazard prioritization, robust station operation, and integrated-energy resilience [14, 22, 37, 43]. No directly comparable study was identified that jointly schedules CGS maintenance personnel and administrative-office employees while incorporating the complete set of human-centered and safety constraints modeled here.

3 Mathematical Model

3.1 Model Generalities

The Gas Company of Qom Province operates nine service locations over the 30-day planning horizon: four gas pressure reduction stations (CGSs) and five administrative offices. The rotational workforce contains 49 employees indexed by i. Each CGS requires one employee per shift, whereas each administrative office requires two employees per shift. Table 1 summarizes these requirements.

Table 1: Staffing requirements and distribution of workstations.

Workstation Type	No. of Locations	Staff per Shift	Total Staff per Shift
Gas pressure reduction stations (CGSs)	4	1	4
Administrative offices	5	2	10
Total	**9**	—	**14**

Each day consists of two 12-hour shifts: a day shift from 07:00 to 19:00 and a night shift from 19:00 to 07:00.

Currently, the scheduling of personnel at the Gas Company of Qom Province is performed manually. Besides being time-consuming, this approach faces several challenges: employee dissatisfaction due to the lack of consideration of shift preferences; sensitivity of some employees to mercaptan gas present in the CGSs; a high incidence of emergency absences; complaints from visitors at customer-facing locations regarding staff interaction; employee dissatisfaction due to commuting distance; excessive overtime for some employees; and employee reluctance to work alongside certain coworkers, which decreases productivity.

After evaluating these conditions, a mathematical model was developed to address the existing problems. Employee preferences for workstation, day, and shift assignments were collected as linguistic judgments and converted to numerical parameters using the centroid procedure described in Section 4.2. Preferences regarding coworkers were coded as $+1$ (willing), -1 (unwilling), and 0 (neutral). Employees with documented mercaptan sensitivity were identified, and each employee's public-communication skill was assessed by multiple supervisors using a predefined rubric.

3.2 Notation and Abbreviations

The following sets, parameters, and decision variables are used throughout the model. All indices, parameters, and variables are defined in Table 2.

3.3 Objective Functions and Constraints

The model contains four objectives and a set of hard operational constraints. Shift-preference and coworker-compatibility scores are first normalized to $[0, 1]$ using their ideal and nadir values so that μ_1 and μ_2 have an interpretable and comparable effect. The normalized weighted satisfaction objective and the remaining objectives are given below.

Table 2: Sets, parameters, and decision variables.

Symbol	Definition
I	Set of employees; $i, i' \in I$
J	Set of service locations; $j \in J$
D	Set of days in the planning horizon; $d \in D$
K	Set of shifts $\{$day, night$\}$; $k \in K$
$\tilde{p}_{ijdk}$	Fuzzy preference score of employee i for location j, day d, and shift k
$q_{ii'}$	Coworker preference: $+1$ willing, -1 unwilling, 0 neutral
g_j	1 if mercaptan exposure is present at location j; 0 otherwise
a_i	1 if employee i is sensitive to mercaptan; 0 otherwise
$\tilde{e}_i$	Fuzzy public-communication skill score of employee i
c_j	1 if location j is customer-facing; 0 otherwise
h_i	Approved standard working hours of employee i
r_{jdk}	Employees required at location j on day d in shift k
dist_{ij}	Distance (km) from employee i's residence to location j
μ_1, μ_2	Weights of normalized shift preference and coworker compatibility; $\mu_1 + \mu_2 = 1$
T_{max}	Maximum allowable working hours per employee in the planning horizon
x_{ijdk}	1 if employee i is assigned to location j on day d in shift k; 0 otherwise
$y_{ii'jdk}$	1 if employees i and i' are co-assigned to the same location/day/shift; 0 otherwise
z_i	Total working hours of employee i
o_i	Overtime hours of employee i

$$\max\ Z_1 = \mu_1 S_{\text{shift}} + \mu_2 S_{\text{cow}}, \quad \mu_1 + \mu_2 = 1 \tag{1}$$

$$S_{\text{shift}} = \frac{\sum_i \sum_j \sum_d \sum_k p_{ijdk}\, x_{ijdk} - L_{\text{shift}}}{U_{\text{shift}} - L_{\text{shift}}} \tag{2}$$

$$S_{\text{cow}} = \frac{\sum_{i<i'} \sum_j \sum_d \sum_k q_{ii'}\, y_{ii'jdk} - L_{\text{cow}}}{U_{\text{cow}} - L_{\text{cow}}} \tag{3}$$

$$\min\ Z_2 = \sum_i \sum_j \sum_d \sum_k \text{dist}_{ij}\, x_{ijdk} \tag{4}$$

$$\min\ Z_3 = \sum_i o_i \tag{5}$$

$$\max\ Z_4 = \sum_i \sum_j \sum_d \sum_k c_j\, e_i\, x_{ijdk} \tag{6}$$

Subject to:

$$\sum_j \sum_k x_{ijdk} \le 1, \qquad \forall\, i,\, d \tag{7}$$

$$\sum_i x_{ijdk} = r_{jdk}, \qquad \forall\, j,\, d,\, k \tag{8}$$

$$\sum_j x_{ijd,\text{day}} + \sum_j x_{ijd,\text{night}} \le 1, \qquad \forall\, i,\, d \tag{9}$$

$$\sum_j x_{ijd,\text{night}} + \sum_j x_{ij(d+1),\text{day}} \le 1, \qquad \forall\, i,\, d < |D| \tag{10}$$

$$\sum_j x_{ij(d-1),\text{night}} + \sum_j x_{ijd,\text{day}} \le 1, \qquad \forall\, i,\, d > 1 \tag{11}$$

$$\sum_{t=d}^{d+4} \sum_j \sum_k x_{ijtk} \le 4, \qquad \forall\, i,\, d = 1, \ldots, |D| - 4 \tag{12}$$

$$h_i \le 12 \sum_j \sum_d \sum_k x_{ijdk} \le T_{\text{max}}, \qquad \forall\, i \tag{13}$$

$$y_{ii'jdk} \le x_{ijdk}, \qquad \forall\, i < i',\, j,\, d,\, k \tag{14}$$

$$y_{ii'jdk} \le x_{i'jdk}, \qquad \forall\, i < i',\, j,\, d,\, k \tag{15}$$

$$y_{ii'jdk} \ge x_{ijdk} + x_{i'jdk} - 1, \qquad \forall\, i < i',\, j,\, d,\, k \tag{16}$$

$$y_{ii'jdk} = 0, \qquad \forall\, i \ge i',\, j,\, d,\, k \tag{17}$$

$$z_i = 12 \sum_j \sum_d \sum_k x_{ijdk}, \qquad \forall\, i \tag{18}$$

$$o_i \ge z_i - h_i, \quad o_i \ge 0, \qquad \forall\, i \tag{19}$$

$$x_{ijdk} \le 2 - a_i - g_j, \qquad \forall\, i,\, j,\, d,\, k \tag{20}$$

$$x_{ijdk} \in \{0, 1\}, \qquad \forall\, i,\, j,\, d,\, k \tag{21}$$

$$y_{ii'jdk} \in \{0,1\}, \qquad \forall\, i < i',\, j,\, d,\, k \tag{22}$$
$$z_i \geq 0, \qquad \forall\, i \tag{23}$$
$$o_i \geq 0, \qquad \forall\, i \tag{24}$$

Objective (1) maximizes a normalized combination of assignment preference and coworker compatibility. Objectives (4)–(6) respectively minimize commuting distance, minimize overtime, and maximize the placement of employees with stronger communication skills at customer-facing locations. Constraint (7) permits at most one assignment per employee per day, and Constraint (8) satisfies location-specific staffing demand. Constraints (9)–(11) enforce within-day and night-to-day rest requirements. Constraint (12) limits each employee to at most four working days in any rolling five-day window. Constraint (13) enforces the approved lower and upper workload bounds. Constraints (14)–(16) are the standard linearization of $y_{ii'jdk} = x_{ijdk}\, x_{i'jdk}$ for unordered employee pairs. Constraint (17) is a symmetry-breaking definition: y variables are created only for $i < i'$ and are fixed to zero otherwise. Constraints (18) and (19) define total hours and overtime. Constraint (20) is the mercaptan-safety restriction: when $a_i = g_j = 1$, the right-hand side is zero and the assignment is prohibited. Constraints (21)–(24) define binary and nonnegative variable domains.

4 Case Study and Data

Iran's high-pressure transmission network delivers processed natural gas to city-entry pressure-reduction facilities before distribution to residential, commercial, and industrial users. The case study concerns nine Qom Province service locations. Initially, records for 56 employees were reviewed; seven were excluded because their preference questionnaires and specialized-skill assessments were incomplete. The final model therefore used 49 complete employee records. Exclusion was based solely on data completeness, not on performance or scheduling outcomes.

The nine service locations are:

- **Ghanavat Station:** Kilometer 5, Ghanavat Road, Emamzadegan Tayeb and Taher Road.
- **Central Station:** Imam Ali Ring Road towards Shah Jamal, after the railway bridge at the beginning of Mahdiabad Road.
- **Thermal Power Plant Station:** Arak Road, adjacent to the Combined Cycle Power Plant.
- **Selfchegan Station:** Selfchegan Road, beginning of Yekeh Bagh Road.
- **Dastjerd Office:** Beginning of Dastjerd Road.

- **Central Office:** Between Imam Square and Martyr Zeyn al-Din Square, Alley 18, Gas Company of Qom Province.
- **District 1 Office:** Corner of Janbazaan Square.
- **District 3 Office:** Salariyeh, Imam Sajjad Street.
- **Pardisan Office:** Pardisan, Hani ibn Urwah Street, next to Fire Department.

The four CGSs must be continuously monitored and maintained by qualified personnel. The five administrative offices provide regional and customer-facing services. Figure 1 shows the locations used in the case study.

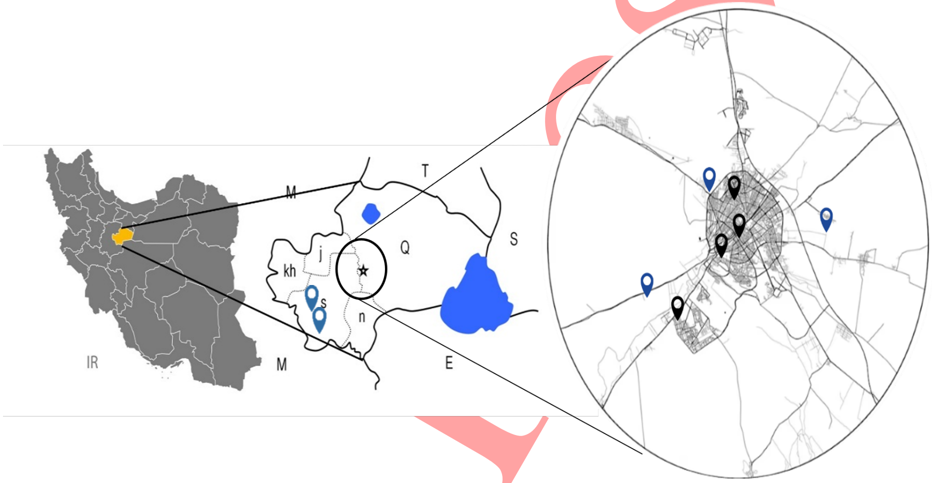


Figure 1: Locations of gas pressure reduction stations and Gas Company offices in Qom Province. Blue markers denote the four gas pressure reduction stations; black markers denote the five administrative offices.

4.1 Data Collection, Anonymization, and Ethical Considerations

Employee data were collected with the Gas Company of Qom Province as part of an internal scheduling-improvement initiative. Shift and location preferences, as well as coworker preferences, were obtained through structured questionnaires. Mercaptan sensitivity was taken from existing occupational-health and safety records. All direct identifiers were removed before analysis, and employees were represented by anonymous codes. Participation in the questionnaire component was voluntary, and informed consent was obtained for research use of anonymized and aggregated data. Communication and public-interaction skills were assessed independently by more than one supervisor using a rubric covering clarity, responsiveness, and effectiveness in handling customer issues.

4.2 Solution Methodology

A two-phase solution framework is employed. First, the multi-objective model is scalarized using the ε-constraint method. Second, the resulting single-objective subproblems are solved using GWO and CSA. A commercial MILP solver is used as an exact baseline for reduced instances and selected ε-subproblems, while the metaheuristics are used for the full-scale case where exact solution becomes computationally demanding.

The fuzzy parameters $\tilde{p}_{ijdk}$ and $\tilde{e}_i$ are represented by triangular fuzzy numbers (l, m, u) and defuzzified by the centroid formula $v = (l+m+u)/3$. For example, a "high" communication rating encoded as $(0.50, 0.75, 1.00)$ produces the crisp value $(0.50 + 0.75 + 1.00)/3 = 0.75$. Table 3 provides the explicit coding used for reproducibility; the same procedure is applied to linguistic shift/location preferences before normalization.

Table 3: Triangular fuzzy coding and centroid defuzzification.

Linguistic rating	**Triangular fuzzy number** (l, m, u)	**Crisp centroid**
Very low	$(0.00,\ 0.00,\ 0.25)$	0.083
Low	$(0.00,\ 0.25,\ 0.50)$	0.250
Medium	$(0.25,\ 0.50,\ 0.75)$	0.500
High	$(0.50,\ 0.75,\ 1.00)$	0.750
Very high	$(0.75,\ 1.00,\ 1.00)$	0.917

4.2.1 Problem Size and Solver Feasibility

After pairwise linearization, $|x|$ grows as $|I||J||D||K|$ and $|y|$ grows as $|I|(|I|-1)|J||D||K|/2$. The y variables therefore dominate model size. To tighten the MILP, only unordered employee pairs $i < i'$ are generated; self-pairs and duplicate pair orderings are eliminated by Constraint (17). Variables that are infeasible a priori because of mercaptan sensitivity are fixed to zero, and basic coverage/workload bounds are resolved before branch-and-bound. Table 4 summarizes the resulting model sizes.

Table 4: MILP model size after pairwise symmetry reduction.

Instance	$\lvert I\rvert$	$\lvert D\rvert$	$\lvert J\rvert$	$\lvert K\rvert$	$\lvert x\rvert$ binaries	$\lvert y\rvert$ binaries	**Total**
Small	15	7	9	2	1,890	13,230	15,120
Medium-1	25	14	9	2	6,300	75,600	81,900
Medium-2	35	21	9	2	13,230	224,910	238,140
Real case	49	30	9	2	26,460	635,040	**661,500**

As shown in Table 4, the real case contains 26,460 assignment binaries and 635,040 unordered-pair co-assignment binaries, for a total of 661,500 binary variables. Reduced instances can be solved exactly, but several full-size ε configurations exceed practical time or memory limits. This scale motivates the metaheuristic solution stage.

4.2.2 ε-Constraint Method

The ε-constraint approach selects one primary objective and converts the remaining objectives into threshold constraints. By varying the threshold vector, a set of non-dominated trade-off solutions is generated [9, 21]. In this study, overtime minimization is the primary objective, while satisfaction, commuting distance, and communication-skill allocation are bounded secondary objectives:

$$\min\ f_1(x) \tag{25}$$

$$\text{s.t.}\quad x \in X, \tag{26}$$

$$f_2(x) \le \varepsilon_2, \tag{27}$$

$$\vdots$$

$$f_n(x) \le \varepsilon_n. \tag{28}$$

The ε-constraint method proceeds as follows: (i) select one objective as the primary objective; (ii) solve the problem for each objective independently to obtain ideal and nadir values; (iii) partition the range of the secondary objectives into intervals; (iv) resolve the problem for each interval value using the primary objective; (v) collect the resulting Pareto-optimal solutions.

Two levels were used for each secondary-objective policy band, and four representative feasible Pareto solutions were retained after dominance screening. The final schedule is selected from these alternatives according to managerial priorities.

Implementation of the ε-Constraint Method. The primary objective function was selected as minimization of total overtime hours (Objective (5)), due to its direct operational and financial impact. For each secondary objective, the ideal (best) and nadir (worst) values were first obtained by solving the model independently. The interval between these values was then uniformly discretized into two levels, giving employee satisfaction $\varepsilon_1 \in \{85\%, 90\%\}$, commuting distance $\varepsilon_2 \in \{\text{baseline} + 10\%, \text{baseline} + 20\%\}$, and communication skill $\varepsilon_3 \in \{\text{minimum acceptable}, \text{enhanced}\}$. These discretizations yield four Pareto-optimal solutions per ε-sweep. Feasibility was strictly enforced throughout; solutions violating hard constraints were repaired or discarded.

Comparison Framework. All methods are evaluated with the same objective definitions, feasibility requirements, and reported metrics. The MILP baseline solves selected ε-constrained subproblems. GWO and CSA optimize the normalized scalar fitness associated with each ε configuration, with hard constraints enforced by decoding, repair, or rejection. All final solutions were assessed using identical objective definitions and performance metrics.

4.2.3 Gray Wolf Optimizer

The Gray Wolf Optimizer (GWO) is a population-based metaheuristic inspired by the hierarchy and cooperative hunting behavior of gray wolves [23]. Candidate schedules are ranked as alpha, beta, delta, and omega solutions. The three leading solutions guide position updates, while the control parameter balances exploration and exploitation.

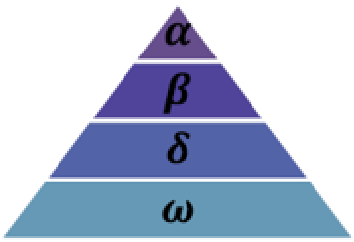


Figure 2: Gray-wolf hierarchy (dominance decreases from top to bottom). Source: adapted from Mirjalili et al. [23].

While hunting, gray wolves surround their prey. The mathematical representation of this encircling behavior is:

$$\mathbf{D} = \mathbf{C} \cdot \mathbf{X}_p(t) - \mathbf{X}(t), \tag{29}$$

$$\mathbf{X}(t+1) = \mathbf{X}_p(t) - \mathbf{A} \cdot \mathbf{D}, \tag{30}$$

where t denotes the current iteration; $\mathbf{A}$ and $\mathbf{C}$ denote the coefficient vectors; $\mathbf{X}_p$ represents the position vector of the prey; and $\mathbf{X}$ denotes the position vector of a gray wolf. The coefficient vectors are calculated as:

$$\mathbf{A} = 2\mathbf{a} \cdot \mathbf{r}_1 - \mathbf{a}, \tag{31}$$

$$\mathbf{C} = 2 \cdot \mathbf{r}_2, \tag{32}$$

where the components of $\mathbf{a}$ are linearly decreased from 2 to 0 throughout the iterations, and $\mathbf{r}_1$, $\mathbf{r}_2$ are random vectors in $[0, 1]$. A two-dimensional position vector and its possible neighboring positions are illustrated in Figure 3.

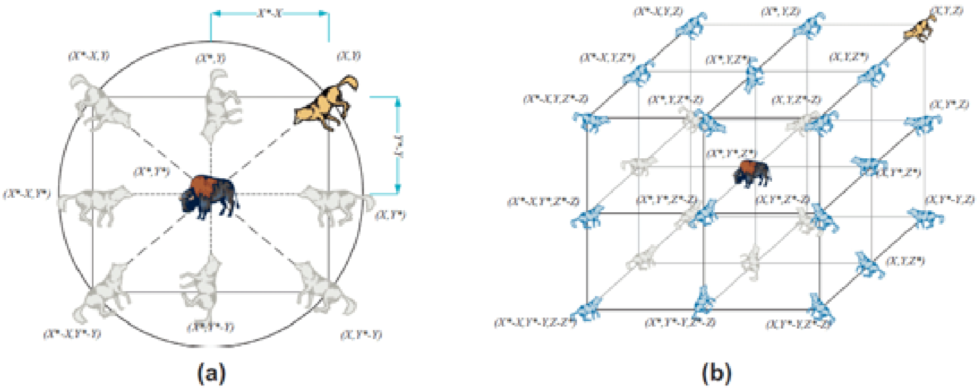


Figure 3: Two- and three-dimensional position vectors and possible locations. Source: adapted from Mirjalili et al. [23].

The top three solutions (alpha, beta, delta) are retained, and the remaining agents update their positions according to:

$$\mathbf{D}_\alpha = \mathbf{C}_1 \cdot \mathbf{X}_\alpha - \mathbf{X}, \quad \mathbf{D}_\beta = \mathbf{C}_2 \cdot \mathbf{X}_\beta - \mathbf{X}, \quad \mathbf{D}_\delta = \mathbf{C}_3 \cdot \mathbf{X}_\delta - \mathbf{X}, \tag{33}$$

$$\mathbf{X}_1 = \mathbf{X}_\alpha - \mathbf{A}_1 \cdot \mathbf{D}_\alpha, \quad \mathbf{X}_2 = \mathbf{X}_\beta - \mathbf{A}_2 \cdot \mathbf{D}_\beta, \quad \mathbf{X}_3 = \mathbf{X}_\delta - \mathbf{A}_3 \cdot \mathbf{D}_\delta, \tag{34}$$

$$\mathbf{X}(t+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3}. \tag{35}$$

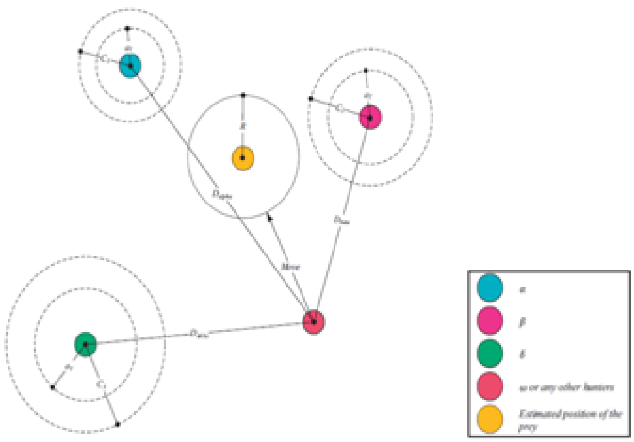


Figure 4: Position updating in GWO. Source: adapted from Mirjalili et al. [23].

4.2.4 Crow Search Algorithm

The Crow Search Algorithm (CSA) is a population-based metaheuristic inspired by the food-hiding and memory behavior of crows [2]. Each crow represents a decoded employee schedule.

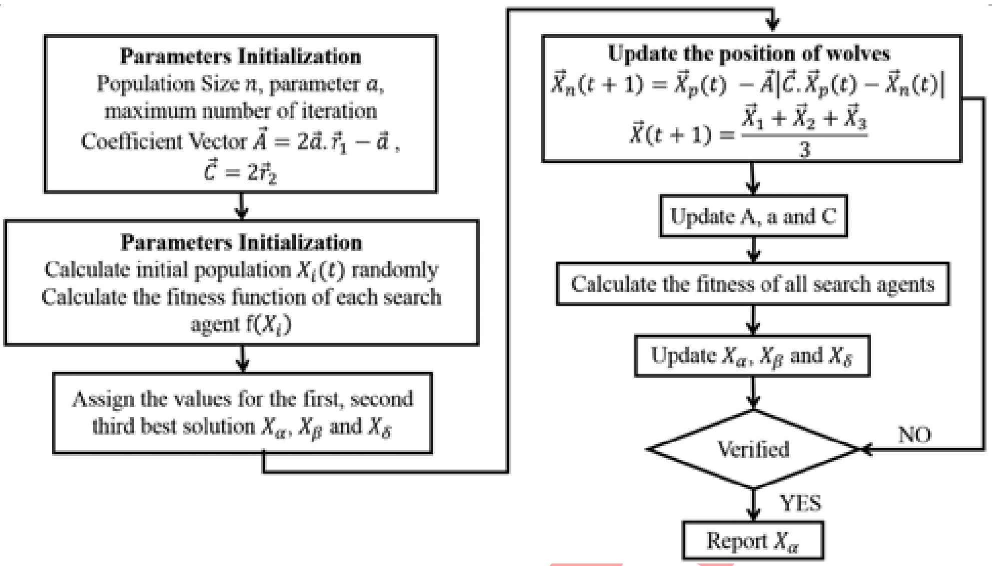


Figure 5: GWO flowchart. Source: adapted from Mirjalili et al. [23].

Flight length controls the step size, while awareness probability determines whether a crow follows another memory position or moves to a random feasible region.

In describing the CSA, a d-dimensional search space containing N crows is considered [2]. The position of crow i at iteration t is represented by the vector $\mathbf{x}^{i,t} = (x_1^{i,t}, x_2^{i,t}, \ldots, x_d^{i,t})$. Each crow maintains a memory $\mathbf{m}^{i,t}$ of the best position found so far. Two scenarios arise when crow i decides to follow crow j:

Scenario 1 (unaware of being chased): Crow j does not know it is being followed. The new position of crow i is:

$$\mathbf{x}^{i,\text{iter}+1} = \mathbf{x}^{i,\text{iter}} + r_i \times fl^{i,\text{iter}} \times \left(\mathbf{m}^{j,\text{iter}} - \mathbf{x}^{i,\text{iter}}\right), \tag{36}$$

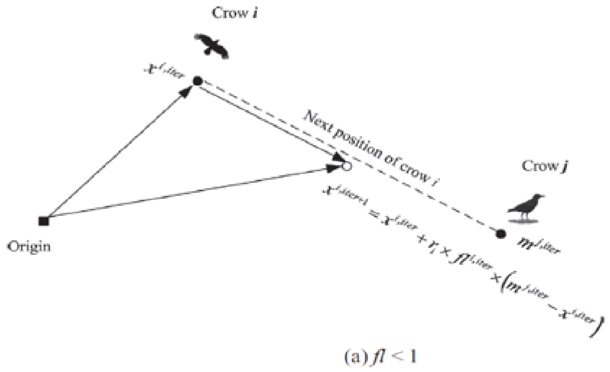
where r_i is a uniform random number in $[0, 1]$ and $fl^{i,t}$ is the flight length of crow i at iteration t. The effect of $fl^{i,t}$ on the search capability is illustrated in Figure 6: small values promote local search, whereas large values promote global search.

Scenario 2 (aware of being chased): Crow j detects crow i and moves to a random position. The general update rule is:

$$\mathbf{x}^{i,\text{iter}+1} = \begin{cases} \mathbf{x}^{i,\text{iter}} + r_i \times fl^{i,\text{iter}} \times \left(\mathbf{m}^{j,\text{iter}} - \mathbf{x}^{i,\text{iter}}\right), & \text{if } r_j \geq AP^{j,\text{iter}}, \\ \text{a random position}, & \text{otherwise}, \end{cases} \tag{37}$$

where $AP^{j,\text{iter}}$ is the awareness probability of crow j at iteration iter. Low AP values increase intensification; high AP values increase diversification.

The memory update rule is:



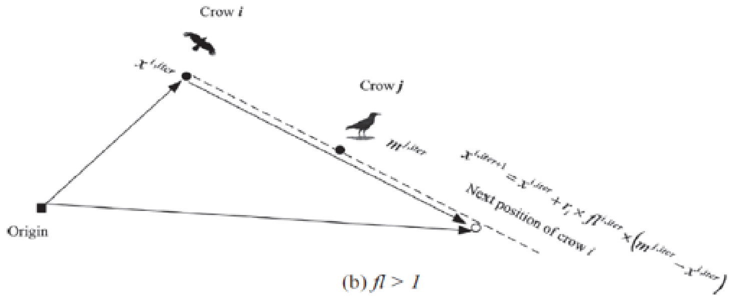


Figure 6: CSA state-1 movement for short and long flight lengths. Source: adapted from Askarzadeh [2].

$$\mathbf{m}^{i,\text{iter}+1} = \begin{cases} \mathbf{x}^{i,\text{iter}+1}, & \text{if } f(\mathbf{x}^{i,\text{iter}+1}) \text{ is better than } f(\mathbf{m}^{i,\text{iter}}), \\ \mathbf{m}^{i,\text{iter}}, & \text{otherwise.} \end{cases} \tag{38}$$

4.2.5 Algorithm Parameter Settings and Implementation Details

To ensure reproducibility, the parameter settings are explicitly reported. For GWO, the population size was set to 30 and the maximum number of iterations to 300. The control parameter **a** was decreased linearly from 2 to 0. For CSA, the flock size was also set to 30 with 300 maximum iterations, awareness probability $AP = 0.1$, and flight length fl drawn from $U[1, 2]$. Both algorithms used the same stopping criterion: maximum iterations reached or no improvement for 50 consecutive iterations. All algorithms were implemented in MATLAB and executed on an Intel Core i7 system with 16 GB of RAM. Each experiment was repeated over 30 independent runs using different random seeds, and all reported performance indicators are expressed as mean ± standard deviation.

4.2.6 Problem-Specific Adaptation and Solution Encoding

Each search agent represents a complete monthly shift schedule encoded as a binary assignment matrix corresponding directly to x_{ijdk}. Since GWO and CSA operate in continuous search spaces, position vectors are transformed into binary assignment decisions using a threshold-based discretization, followed by the repair procedure described in Section 4.2.7. The coworker co-assignment variables $y_{ii'jdk}$ are not explicitly encoded but are implicitly derived during fitness evaluation by identifying co-assigned employee pairs.

4.2.7 Feasibility Repair Operator

After discretization, some candidates may violate hard constraints. The feasibility repair operator is applied in the following priority order:

Step 1 (Mercaptan sensitivity – Constraint (20)): Assignments of mercaptan-sensitive employees to CGS stations are removed immediately and replaced via reassignment or swap; if neither is possible, the employee remains unassigned for the period.

Step 2 (Demand satisfaction – Constraint (8)): For each staffing deficit, eligible unassigned employees are assigned in order of lowest additional penalty (overtime increase and commuting distance).

Step 3 (At most one assignment per day – Constraint (7)): Duplicate assignments are resolved by retaining the best-contributing one; deficits are then restored via Step 2.

Step 4 (Rest rules – Constraints (9)–(11)): Forbidden consecutive shift patterns are removed (lowest-priority assignment) and Step 2 is re-applied.

Step 5 (Maximum consecutive working days – Constraint (12)): A rest day is created by removing the lowest-priority assignment within the violating window; Step 2 is re-applied.

Step 6 (Working hours and overtime – Constraints (13) and (19)): Excess assignments are replaced by under-utilized eligible employees via Step 2.

Steps 1–6 are repeated for at most R repair iterations. If the schedule remains infeasible, the candidate is discarded.

5 Results and Discussion

5.1 Consistent Evaluation Metrics

To ensure comparability across solution methods, all solutions were evaluated using: (i) average total working hours; (ii) average overtime hours; (iii) shift preference satisfaction rate;

(iv) coworker preference satisfaction rate; (v) compliance with mercaptan sensitivity constraints; and (vi) average computational time.

Shift preference satisfaction (%) is computed as the sum of defuzzified preference scores over all actual assignments, normalized by the maximum achievable shift-preference score under the same hard constraints.

Coworker preference satisfaction (%) is computed as the sum of $q_{ii'}$ values for all co-assigned employee pairs in the final schedule, normalized by the maximum achievable coworker-preference score under the same feasibility constraints.

Table 5 summarizes the case-study and algorithm parameters.

Table 5: Case-study and algorithm parameters.

Parameter	Description	Value
Number of employees	Total rotating staff members	49
Number of stations	Total service locations	9 (4 CGS + 5 Admin)
Planning horizon	Number of working days	30
Shifts per day	Day (07:00–19:00), Night (19:00–07:00)	2
Staffing per shift	CGS: 1 worker; Administrative: 2 workers	—
Standard working hours	Normal monthly hours per employee	192 h
Commuting distance	Employee residence to station	2 to 45 km
Mercaptan-sensitive employees	Restricted from all 4 CGS stations	5
Importance weights	$\mu_1 = \mu_2$ (baseline)	0.5 each
GWO/CSA population size	Number of wolves/crows	30
Maximum iterations	Stopping criterion	300
Independent runs	For statistical comparison	30

5.2 Computational Time Comparison

Table 6 presents the average runtime under the same computational environment.

Table 6: Computational time comparison.

Approach	Average time (s)
ε-constraint baseline (single ε-subproblem)	145
GWO	121.4 ± 6.5
CSA	109.8 ± 5.1

5.3 Statistical Comparison

Table 7 presents the statistical comparison of GWO and CSA over 30 independent runs. The Wilcoxon signed-rank test was applied to paired outcomes because normality cannot be assumed for metaheuristic results; differences are statistically significant at $\alpha = 0.05$ for all principal metrics.

Table 7: Statistical comparison of GWO and CSA over 30 independent runs.

Metric	Method	Mean	Std. Dev.
Average overtime hours (h)	GWO	48.6	3.9
	CSA	44.2	2.7
Shift preference satisfaction (%)	GWO	87.3	2.8
	CSA	90.1	1.9
Coworker preference satisfaction (%)	GWO	83.6	3.1
	CSA	86.4	2.2
Average computational time (s)	GWO	121.4	6.5
	CSA	109.8	5.1

5.4 Workload and Commute Fairness

Fairness was evaluated using the Gini coefficient, which ranges from 0 (perfect equality) to 1 (maximum inequality). Let $\mathbf{v} = (v_1, v_2, \ldots, v_n)$ denote a nonnegative employee-level vector sorted in ascending order. The Gini coefficient is:

$$G(\mathbf{v}) = \frac{2\sum_{i=1}^{n} i\, v_i}{n\sum_{i=1}^{n} v_i} - \frac{n+1}{n}. \tag{39}$$

This metric has been widely used to assess allocation inequality and fairness–attractiveness trade-offs in scheduling and dispatching problems [6, 38]. Table 8 reports the Gini-based fairness indicators for the selected final schedule.

Table 8: Gini-based fairness indicators for the selected final schedule.

Fairness measure	Employee-level vector	Gini coefficient
Workload fairness	Total scheduled hours z_i, $i = 1, \ldots, 49$	0.012
Commute fairness	Cumulative commuting distance per employee	0.226

The workload Gini coefficient is 0.012, indicating a highly equitable distribution of total scheduled working hours (employees were assigned between 216 and 228 working hours). The commute Gini coefficient is 0.226, reflecting greater dispersion due to the geographic distribution of employees' residences and service locations.

5.5 Sensitivity Analysis of Preference Weights

Table 9 reports the sensitivity analysis obtained by varying μ_1 and μ_2. All values were generated with CSA over 30 independent runs under otherwise identical settings.

Table 9: Sensitivity analysis of preference weights.

μ_1	μ_2	Shift Satisfaction (%)	Coworker Satisfaction (%)	Avg. Overtime (h)
0.8	0.2	95	75	58
0.6	0.4	91	82	54
0.5	0.5	89	85	52
0.4	0.6	85	88	50
0.2	0.8	80	90	48

The sensitivity results reveal a clear trade-off: moving from $(\mu_1, \mu_2) = (0.8, 0.2)$ to $(0.2, 0.8)$ lowers shift satisfaction from 95% to 80%, raises coworker satisfaction from 75% to 90%, and lowers average overtime from 58 h to 48 h. Decision-makers should therefore select weights according to whether individual schedule preference or team compatibility is the more critical operational priority. Higher μ_2 is especially effective in high-pressure, continuous-operation contexts such as gas supply systems, where teamwork quality directly influences overtime accumulation and operational reliability.

6 Conclusion

This study developed and evaluated a multi-objective MILP model for rotational shift scheduling in gas distribution operations. Applied to 49 employees, nine locations, and a 30-day horizon, the model jointly represents coverage, rest and workload rules, employee preferences, coworker compatibility, commute distance, public-communication skills, and mercaptan-safety exclusions. The ε-constraint framework structures the objective trade-offs, while GWO and CSA provide computationally practical solutions for the full-scale instance. Across 30 runs, CSA produced lower overtime, higher preference satisfaction, and shorter runtime than GWO, with statistically significant paired differences at the 5% level. Sensitivity analysis showed that stronger emphasis on coworker compatibility coincided with lower overtime—a result with direct managerial relevance for continuous and safety-critical operations.

The main managerial implication is that workforce planning need not treat operational coverage and employee-centered considerations as separate decisions. The model enables planners to examine explicit trade-offs and select a feasible schedule consistent with safety and human-resource priorities. Its modular structure can be transferred to other utilities by replacing staffing demand, shift structure, labor rules, distance matrices, skill indicators, and hazard restrictions.

The study has five principal limitations. First, employee preferences are assumed stable during the planning horizon. Second, emergency absences, equipment failures, and supply disruptions are not modeled. Third, centroid defuzzification converts ambiguous linguistic judgments to single deterministic values and therefore discards residual uncertainty. Fourth, validation is limited to one provincial organization. Fifth, seven incomplete records were excluded, which may create selection bias.

Future research should develop stochastic or robust formulations for uncertain attendance and demand, incorporate on-call pools and disruption recovery, and test rolling-horizon or multi-period scheduling for seasonal gas demand. Machine-learning methods could dynamically predict changing employee preferences from historical roster choices, provided that privacy, explainability, and human oversight are preserved.

Declarations

Availability of Supporting Data

The data that support the findings of this study are available from the corresponding author upon reasonable request. Due to organizational confidentiality, the data are not publicly available.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Authors Contributions

Mohammad Javad Pahlevanzadeh: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Writing – Original Draft, Visualization. **Mohammad Reza Fathi**: Conceptualization, Methodology, Supervision, Writing – Review & Editing. **Amirhossein Saffarinia**: Data Curation, Validation, Writing – Review & Editing.

Artificial Intelligence Statement

OpenAI ChatGPT was used for language editing and reference-formatting support. AI tools were not used to create or alter employee data, optimization outputs, or statistical results.

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