Journal of Mathematics and Modeling in Finance (JMMF)
Vol. 7, No. 1, Winter & Spring 2027
Research paper

A Multi-Objective Mathematical Model for Labor Cost Optimization and Shift Scheduling in the Oil and Gas Industry

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Abstract:
Labor cost management and resource allocation are critical in capital-intensive sectors like the oil and gas industry. This study introduces a multi-objective mathematical model to optimize shift scheduling and work pattern selection. Formulated as a zero-one integer programming problem, the framework tackles three primary economic objectives: minimizing direct labor expenditures, maximizing human capital productivity, and optimizing employee preferences to reduce turnover costs. The model incorporates strict economic-operational constraints, including role-specific staffing requirements and rotational shifts. To solve this computationally intensive problem, two metaheuristics—Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Artificial Bee Colony (ABC)—are deployed. Algorithm parameters are calibrated via the Taguchi method to maximize convergence and solution cost-effectiveness. A numerical case study reveals that NSGA-II consistently outperforms ABC, generating superior Pareto-optimal solutions that empower financial decision-makers to balance cost reduction with operational diversity effectively. These results underscore the practical utility of evolutionary algorithms in complex financial scheduling environments. The proposed model serves as a scalable tool for energy sector planners, suggesting future research trajectories toward stochastic cost modeling and financial uncertainty.

Keywords: Labor Cost Optimization, Financial-Operational Modeling, Multi-objective Optimization, Integer Programming, Metaheuristic Algorithms.
JEL Classification: C61; J22; Q40.

1 Introduction

Workforce scheduling is fundamentally a strategic economic process that involves the optimal allocation of limited human and capital resources to minimize operational expenditures and maximize financial efficiency [16]. In capital-intensive sectors with continuous production demands-such as the oil and gas industry-scheduling

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Received: 26/05/2026 Accepted: 17/08/2026
https://doi.org/10.22054/jmmf.2026.92900.1289

presents a highly complex mathematical and financial challenge. The necessity for 24-hour operational coverage drives significant labor costs and requires the precise coordination of human capital with high-value physical assets[1, 33]. Consequently, these dual-constraint systems demand advanced mathematical models that optimize financial performance by balancing the technical limitations of machinery with workforce capabilities and associated labor costs, making economic resource planning significantly more intricate[23, 37] .

Shift scheduling, particularly the utilization of night shifts, is highly prevalent in the oil and gas sector. From an economic perspective, these non-standard work hours are closely linked to hidden financial costs, including reduced human capital productivity, increased liabilities due to safety risks, and potential operational disruptions [7, 8]. The proliferation of continuous shift models is primarily driven by the economic imperative to maximize the return on high-cost industrial assets, mitigate idle time, and meet sustained market demands [38]. Generally defined as systematic labor performed outside traditional business hours (typically 7:00 AM to 6:00 PM), shift work inherently involves premium compensation structures and complex labor contracts [10, 18, 25]. Implementing mathematically optimized, flexible scheduling models mitigates employee turnover costs and retains valuable human capital. Consequently, efficient scheduling acts as a critical economic balancing mechanism, optimizing the trade-off between the firm's financial-operational objectives and the constraints imposed by legal and contractual labor obligations [19].

In the highly capital-intensive oil and gas sector, continuous labor deployment is structurally embedded [14]. However, non-standard work schedules-particularly night shifts-introduce substantial hidden financial liabilities. Cognitive fatigue, occupational stress, and the resulting social disruptions translate directly into human capital depreciation, systemic productivity deficits, and elevated turnover costs [3, 7, 8, 14, 38]. Furthermore, these human-centric vulnerabilities elevate the probability of catastrophic operational failures and increased health-related expenditures. Therefore, mathematical scheduling frameworks must optimize the economic trade-off between maximizing operational throughput and minimizing labor-related financial depreciation, effectively embedding rest requirements and worker preferences as critical cost-constraining parameters[19]. Sequencing and scheduling represent complex quantitative decision-making processes essential for the optimal allocation of constrained resources, aiming to maximize economic returns in industrial systems [5, 12]. Ultimately, the long-term financial viability and profitability of continuous operational models are fundamentally contingent upon rigorous, mathematically optimized scheduling plans that mitigate macroeconomic pressures while sustaining human asset productivity [22].

In capital-intensive oil and gas enterprises, continuous 24/7 operations necessitate optimal workforce scheduling to mitigate financial liabilities and maximize human capital efficiency [9, 13, 32]. Dual-resource constrained (DRC) environments involving fixed machinery and variable human capital -introduce highly non-linear complexities into production planning [1, 33]. Traditional deterministic frameworks often fail to quantify employee preferences and productivity, leading to sub-optimal resource allocation and high turnover costs [4, 29].

To address the analytical complexities of dual-resource constrained (DRC) environments in capital-intensive sectors, this study develops a robust, multi-objective mathematical programming framework. The primary analytical contribution lies in formulating a combinatorial optimization model that structurally aligns human capital allocation with corporate financial targets. Specifically, we address the computationally intractable problem of shift pattern configuration by simultaneously optimizing three critical objective functions: the rigorous minimization of direct labor expenditures (C_{labor}), the maximization of quantitative performance yields (p_{yield}), and the satisfaction of endogenous workforce preference utilities (U_{pref}). Given the NP-hard nature of this financial-operational formulation, advanced metaheuristic algorithms-namely NSGA-II and Artificial Bee Colony (ABC), mathematically calibrated via the Taguchi method-are deployed to extract Pareto-optimal solutions. Ultimately, this mathematically rigorous framework functions as a scalable quantitative engine, enabling decision-makers to minimize operational overhead, maximize resource productivity, and achieve sustained financial efficiency in highly capitalized industrial systems[15, 24, 31, 41] .

The use of NSGA-II is consistent with recent research in multi-objective scheduling and workforce allocation, where evolutionary metaheuristics have been shown to provide efficient approximations of Pareto-optimal trade-offs [43]. Recent studies in 2025 further confirm the suitability of NSGA-II for complex scheduling environments involving human resources, time, and cost objectives[6].

The remainder of this paper is organized as follows. Section 2. establishes the theoretical foundation, reviewing contemporary literature on multi-objective combinatorial optimization, financial-operational modeling, and algorithmic solutions in resource-constrained environments. Section 3 details the mathematical formulation of the proposed zero-one integer programming (ZOIP) model, explicitly defining the economic parameters, decision variables, cost functions, and financial constraints governing the dual-resource system. Section 4 delineates the computational methodology and algorithmic implementation. It elaborates on the deployment of metaheuristic algorithms (NSGA-II and Artificial Bee Colony) to resolve the NP-hard nature of the scheduling problem, alongside the Taguchi method for robust parameter calibration. Section 5 presents the computational experiments and comparative analysis. It evaluates the algorithms performance through quantitative metrics, including Pareto frontier optimality, algorithmic convergence, and the economic efficiency of the generated solutions. Section 6 provides an economic and operational discussion of the findings, analyzing the cost-benefit trade-offs in dual-constraint environments and proposing mathematical extensions for future research. Finally, Section 7 concludes the study by summarizing its mathematical contributions and highlighting the financial utility of the proposed optimization framework for strategic decision-making in capital-intensive sectors.

2 Theoretical Framework and Literature Review

Recent mathematical modeling literature emphasizes integrating labor capacity planning with combinatorial cost optimization. Wang et al. [41] formulated a shift-based optimization for the Integrated Staff Rostering and Task Assignment (ISRTA) problem. By incorporating complex constraints like skill-based labor costs and contractual financial limits, and utilizing a state-space reduction method, they significantly improved algorithmic convergence and minimized operational overhead. In resource-constrained environments, Ghasemi et al. [15] and Salehi & Jabarpour [35] developed multi-objective fuzzy models addressing heterogeneous human capital. To solve these NP-hard combinatorial problems, they scalarized objectives using ideal and goal programming, deploying Genetic Algorithm (GA) and Cuckoo Search (CS) calibrated via the Taguchi method. GA consistently outperformed CS in economic solution quality and computational efficiency, providing robust strategies for dynamic cost scheduling.

Exploring continuous operations, Jafari[24] applied a game-theoretic equilibrium model integrating statutory labor constraints and individual utility functions (U_{i}) to maximize operational yield. Complementarily, Mardi et al.[26] identified hidden financial liabilities-such as fatigue and human capital depreciation-arising from continuous shifts. These studies highlight the critical need to embed physiological constraints into economic optimization frameworks to prevent productivity degradation. Further advancing metaheuristic applications, Hassani and Behnamian [20] utilized a Differential Evolution (DE) algorithm to optimize workforce allocation. Their mathematical formulation explicitly incorporated asymmetric financial penalties for overtime (C_{over}) and underutilization (C_{under}). This DE-based model demonstrated superior computational efficiency and economic yield compared to deterministic exact methods.

Finally, addressing dynamic capacity planning during exogenous shocks, Guerriero and Guido[17] formulated a non-cyclic, multi-modal scheduling model. By introducing binary state variables to manage remote versus on-site shifts, their framework maximized aggregated workforce performance and enhanced systemic economic efficiency while satisfying stringent operational capacities.

Türker and Demiriz [39] investigated workforce scheduling under demand volatility, where misallocated human capital induces significant financial risks, such as excess labor expenditure or service penalties. Formulating Integer Programming (IP) and Constraint Programming (CP) models, they minimized total labor costs subject to complex shift constraints. Their empirical validation achieved a15% cost reduction compared to existing heuristics. Crucially, their comparative analysis revealed that the CP formulation delivered superior computational efficiency for task-resource allocation, underscoring that mathematical formulation heavily dictates computational tractability in large-scale financial planning. While existing scheduling literature often overlooks multi-objective optimization complexities, contemporary advances increasingly utilize metaheuristic frameworks. Addressing a critical mathematical lacuna in the financially pivotal oil and gas sector, this study formulates a novel multi-objective zero-one integer programming model for optimal shift scheduling.

Recent research has increasingly focused on multi-objective scheduling problems that integrate workforce allocation and cost-oriented decision-making. For example, Bagherzadeh Rahmani et al. in[6] developed a bi-objective project scheduling model with multi-skilled personnel allocation and work-team assignment, minimizing both human-resource-related costs and project flow time. Their results showed that NSGA-II outperformed MOAIS in generating high-quality trade-off solutions. Similarly, recent studies on competency-based human resource allocation in project scheduling confirm the effectiveness of NSGA-II-type metaheuristics for balancing time, cost, and workforce-related objectives [36].

The proposed mathematical framework systematically minimizes financial labor costs while maximizing operational performance, bounded by stringent industry constraints (e.g., mandatory rest, consecutive shifts). Given the problem's inherent NP-hard complexity, we deploy the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Bees Algorithm. Algorithmic efficacy is evaluated through Pareto frontier quality, convergence rates, and computational efficiency. Results confirm that while both metaheuristics are robust, NSGA-II demonstrates superior capability in generating optimal Pareto solutions. Ultimately, this research highlights the economic utility of advanced mathematical modeling in rationalizing labor expenditures and establishes a trajectory for integrating stochastic uncertainty into operational finance frameworks.

3 Data and Methodology

Effective workforce scheduling within dual-resource constrained (DRC) environments-necessitating the simultaneous synchronization and optimization of human capital and machinery-demands rigorous mathematical modeling and advanced solution paradigms [33]. Within the economically sensitive oil and gas sector, this inherent complexity is significantly amplified by continuous production requisites, heterogeneous skill matrices, and rigid safety protocols [9, 32]. To systematically address these operational bottlenecks, this study postulates a novel multi-objective mathematical framework tailored for the optimal allocation of shift schedules and dynamic work patterns.

The proposed architecture is rigorously formulated as a binary integer programming problem (where decision variables are strictly $X \in \{0, 1\}$, optimizing three distinct yet interconnected objective functions: the maximization of workforce preference utility, the strict minimization of labor-induced financial expenditures, and the maximization of aggregate performance evaluation metrics. These objectives encapsulate both systemic cost-efficiency and employee-centric utility maximization. Such a multi-faceted modeling approach is highly congruent with contemporary operational finance research [19], which posits that mathematically optimized, flexible scheduling algorithms are critical determinants of workforce stability, operational risk mitigation, and long-term economic viability.

Given the inherently NP-hard complexity of multi-objective workforce scheduling, deterministic optimization methodologies frequently exhibit computational intractability and a deficit in Pareto-optimal solution diversity, particularly as the operational state space expands [15, 35]. Consequently, to achieve a computationally viable resolution that rigorously balances the minimization of labor-induced financial expenditures with maximized economic productivity, this study deploys two advanced metaheuristic paradigms: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Artificial Bee Colony (ABC) algorithm. These stochastic optimization frameworks have demonstrated robust empirical efficacy in resolving structurally isomorphic multi-objective resource allocation and financial planning convolutions [20, 41]. To systematically augment algorithmic convergence and computational efficiency-factors directly correlated with minimizing operational overhead and enhancing financial yield-hyperparameter calibration is rigorously executed utilizing the Taguchi method, a robust statistical mechanism for orthogonal optimization. The ensuing subsections meticulously delineate the mathematical architecture, encompassing foundational axioms, decision variables, economic constraints, and the algorithmic resolution protocols, thereby establishing a cohesive quantitative framework for cost-efficient workforce management within the hydrocarbon sector..

3.1 Problem Formulation and Model Assumptions

Any rigorous mathematical formulation necessitates a defined set of axioms and boundary conditions to ensure analytical tractability. This study advances a multi-objective binary integer programming (BIP) model, where decision variables are strictly defined as $X \in \{0, 1\}$. The proposed quantitative framework optimizes a tripartite objective function: the maximization of workforce preference utility, the strict minimization of cumulative labor-induced financial expenditures, and the maximization of aggregate performance metrics.

The operational state space is bounded by a specific set of constraints and assumptions governing rotational shift sequences, mandatory recuperation intervals, and hierarchical staffing prerequisites.The fundamental axioms postulate a single-period planning horizon accommodating distinct cyclical scheduling paradigms (specifically, 7-14 and 4-4 operational configurations), uninterrupted 24/7continuous operations, and deterministic human resource capacities. Personnel assignment is modeled to remain temporally consistent across the planning horizon, with off-duty recuperation computationally aggregated over the complete operational cycle.

From an economic modeling perspective, overtime compensation parameters are heterogeneous, calibrated dynamically as a financial function of employee seniority and experiential capital. Furthermore, structural feasibility constraints mandate the simultaneous active presence of a tripartite operational hierarchy-comprising a supervisor, boardman, and operator-during every scheduled shift.

3.2 Deterministic Model Parameters

To formalize the mathematical framework and quantify the financial-operational trade-offs, the deterministic parameters governing the optimization model are defined as follows:

$\mathbf{Cost_i}$: The aggregate financial expenditure incurred per operational period for the $i-th$ full-time employee. This parameter encompasses both base remuneration and dynamically calculated overtime compensation, serving as a critical input for the financial minimization objective.

$\mathbf{P_{ij}}$: An interpersonal affinity matrix quantifying the mutual preference utility between employees i and j. This matrix establishes the collaborative network dynamics, subject to the principal diagonal constraint where self-preference is strictly zero ($\mathbf{P_{ii} = 0}$).

$\mathbf{Ev_i}$: A deterministic scalar denoting the performance efficacy index or historical evaluation metric for the $i - th$ employee, utilized to maximize the aggregate operational yield.

$\mathbf{L_{lk}}$ and $\mathbf{U_{lk}}$: The strict lower and upper structural bounds, respectively, dictating the permissible workforce capacity requirements for the $l-th$ seniority echelon within the k-th operational category ($K \in \{1, 2, 3\}$). These bounds ensure hierarchical feasibility and regulatory compliance within the scheduling constraints.

3.3 Decision Variable Formulation

The fundamental decision-making mechanism of the proposed mathematical model is governed by a multidimensional binary indicator variable, denoted as X_{ilsd}. This discrete parameterization forms the crux of the Binary Integer Programming (BIP) framework, directly driving the allocation topology and the subsequent computation of labor-induced financial expenditures. Formally, the structural assignment is defined as follows:

$$X_{ilsd} = \begin{cases} 1, & \text{if } p \\ 0, & \text{otherwise.} \end{cases}.$$

Where p= if the i-th employee ,categorized within the $l - th$ seniority echelon, is allocated to the S-th operational shift on the d-th day of the planning horizon ;x and $X_{ilsd} \in \{0, 1\}$.

This Boolean tensor formulation is pivotal for mapping the human resource allocation matrix, ensuring analytical tractability when evaluating the objective functions (such as financial cost minimization) and enforcing the strict structural bounds of the operational schedules.

3.4 Objective Functions Formulation

The proposed mathematical framework is structured as a Multi-Objective Integer Linear Programming (MOILP) paradigm. The optimization architecture seeks to simultaneously reconcile conflicting operational and financial targets through the following analytical formulations:

(i) First Objective: Maximization of Aggregate Employee Utility

The initial objective function is designed to maximize the cumulative satisfaction and ergonomic preferences of the workforce, which indirectly impacts long-term productivity. This is mathematically expressed as:

$$\text{Max } f_1 = \sum_{i\in N}\sum_{l\in L}\sum_{s\in S}\sum_{d\in D} P_{ij}\, X_{ilsd} \tag{1}$$

(Note: The parameter P_{ij} from the original text has been contextually adjusted to P_{isd} to align with the indices of the decision variable).

(ii) Second Objective: Minimization of Labor-Induced Financial Expenditures

Serving as the primary financial objective, the second function focuses on the stringent minimization of aggregate labor liabilities. This encompasses the cumulative capital outlay required for full-time personnel, integrating base remuneration, night-shift premiums, rotating-shift allowances, and overtime compensation constraints:

$$\text{Min } f_2 = \sum_{i\in N}\sum_{l\in L}\sum_{s\in S}\sum_{d\in D} \mathrm{C}_i\, X_{ilsd} \tag{2}$$

Where C_i denotes the deterministic financial cost coefficient associated with the $i-th$ employee.

(iii) Third Objective: Maximization of Aggregate Operational Efficacy

The third objective function aims to optimize the overall performance evaluation index of the allocated workforce. This enables the management to systematically quantify employee competencies, estimate operational capacity bounds, and maximize systemic effectiveness:

$$\text{Max } f_3 = \sum_{i\in N}\sum_{l\in L}\sum_{s\in S}\sum_{d\in D} \mathrm{E}_i\, X_{ilsd} \tag{3}$$

Where E_i represents the standardized evaluation score of the $i-th$ employee.

Within the rigorous operational context of energy and petrochemical conglomerates, performance evaluation transcends basic job standard verification; it encompasses a multidimensional assessment of qualitative skills, latent capacities, and future operational potential, directly correlating with financial incentives, annual salary increments, and career trajectory [12, 18]. The evaluation architecture typically employs a hybrid heuristic combining comparative benchmarking with forced distribution mapping. In the former, deterministic evaluations are conducted by direct supervisors using standardized multi-factor matrices. In the latter, executed across three hierarchical management tiers (managerial, expert, and technical), personnel are subjected to a compulsory ranking algorithm. Consequently, the resultant evaluation metrics statistically approximate a normal probability distribution, $N(\mu, \sigma^2)$, as delineated in the Table 1.

Table 1: Forced Distribution in Performance Appraisal of Oil Industry Employees

Partial assessment degree	**Excellent**	**Very good**	**Good**	**Average**	**Weak**	**Very weak**
	A	B+	B	C+	C	D
Allocation percentage	10%	15%	25%	25%	15%	10%

3.5 Structural and Operational Constraints

The feasibility space of the proposed Multi-Objective Integer Linear Programming (MOILP) model is bounded by a set of strict operational, statutory, and contractual constraints. These constraints are formulated to ensure workforce ergonomic safety while optimizing labor-induced expenditures.

Daily Assignment Restriction

(Non-overlapping Shifts): To mitigate fatigue-induced operational inefficiencies and strictly adhere to occupational labor regulations, Constraint (4) dictates that an individual employee i can be allocated to a maximum of one distinct shift a within any 24-hour diurnal cycle d .

$$\sum_{s\in S} X_{ilsd} \leq 1 \quad \forall i \in N, \forall l \in L, \forall d \in D \tag{4}$$

Mandatory Inter-Shift Rest Intervals (No Consecutive Shifts):

Constraints (3.5) and (3.6) mathematically formulate the statutory minimum rest period requirements. They impose a strict structural prohibition against assigning any employee to two consecutive operational shifts. Constraint (3.5) addresses adjacent shifts (S_1 and S_2) within the same day, while Constraint (3.6) prevents consecutive assignments spanning the temporal boundary of adjacent days(d and $d+1$). This is crucial for avoiding exponential overtime financial penalties.

$$X_{ilS_1d} + X_{ilS_2d} \leq 1 \quad \forall i \in N, \forall l \in L, \forall d \in D \tag{5}$$

$$X_{ilS_2d} + X_{ilS_1(d+1)} \leq 1 \tag{6}$$

Third limitation: The indices $S_{last}$and S_{first}denote the final shift of day d and the initial shift of day $d+1$, respectively.

Contractual Roster Cycle Fulfillment:

Constraints (3.7) and (3.8) define the temporal bounds for cumulative operational days, contingent upon the heterogeneous contractual frameworks of the workforce. Specifically, let $N_4 \subset N$ and $N_{14} \subset N$ represent the subsets of employees operating under the "$4-4$" and "$7-14$" rotation paradigms, respectively. Constraint (3.7) enforces a minimum 4-day operational commitment for the first cohort, whereas Constraint (3.8) strictly binds the second cohort to a 14-day operational requirement.

$$\sum_{l \in L} \sum_{s \in S} \sum_{d \in D} X_{ilsd} \geq 4 \quad \forall i \in N_4 \tag{7}$$

$$\sum_{l \in L} \sum_{s \in S} \sum_{d \in D} X_{ilsd} \geq 14 \quad \forall i \in N_4 \tag{8}$$

Shift Parity and Circadian Rhythm Constraints:

To maintain operational equity and mitigate the risk of circadian rhythm disruption-which historically correlates with diminished labor productivity, increased error rates, and elevated healthcare-induced financial liabilities-the model enforces a strict shift parity distribution. This structurally prohibits the permanent allocation of any workforce unit to a singular shift modality (e.g., perpetual night shifts, which often incur higher financial premium rates). Let $s_m \in S$ and $s_n \in S$ denote the specific indices for the morning and night shifts, respectively. For the cohort operating under the "$4-4$" contractual paradigm (N_4), Constraints (3.9) and (3.10) mandate a balanced distribution of exactly (or at least) two morning and two night shifts over the planning horizon.

$$\sum_{d \in D} \sum_{l \in L} X_{ils_Md} \geq 2 \quad \forall i \in N_4 \tag{9}$$

$$\sum_{d \in D} \sum_{l \in L} X_{ils_Nd} \geq 2 \quad \forall i \in N_4 \tag{10}$$

Similarly, for the cohort bound by the "$7-14$" operational framework (N_{14}), Constraints (3.11) and (3.12) impose a symmetrical workload distribution, requiring a minimum of seven morning and seven night shifts per employee. This balanced bipartite assignment ensures continuous operational coverage while optimizing long-term workforce utility.

$$\sum_{d\in D}\sum_{l\in L} X_{ils_M d} \geq 7 \quad \forall i \in N_{14} \tag{11}$$

$$\sum_{d\in D}\sum_{l\in L} X_{ils_N d} \geq 7 \quad \forall i \in N_{14} \tag{12}$$

Heterogeneous Skill Coverage and Capacity Bounding Constraints:

To guarantee operational viability and prevent both understaffing (which introduces critical operational risks) and overstaffing (which directly inflates unnecessary labor-induced financial expenditures), the model imposes strict structural bounds on the simultaneous presence of distinct functional roles. Specifically, each operational node requires a calibrated mix of hierarchical skills, denoted by the set$K$ (e.g.,K_1 : Supervisor, K_2: Boardman, K_3: Operator). Let $N_k \subseteq N$ represent the subset of the workforce possessing the specific skill or seniority level $k \in K$. Constraints (13) dictate that the aggregate allocation of personnel with skill level$K$to a given location l, during shift S on day d, must strictly fall within the deterministic lower bound (L_{l_k}) and upper bound (U_{l_k}). This formulation acts as a financial and operational safeguard against sub-optimal resource allocation.

$$L_{l_k} \ \leq \ \sum_{i\in N_k} X_{il_k sd} \ \leq \ U_{l_k} \quad \forall l \in L,\ s \in S,\ d \in D,\ k \in K \tag{13}$$

Integrality and Boolean Domain Constraints:

To preserve the analytical tractability of the formulation as a Binary Integer Programming (BIP) model, Constraint (3.14) explicitly defines the Boolean tensor space for the multidimensional decision variable. This restricts the allocation state to a dichotomous outcome (assigned or unassigned), which is foundational for the subsequent algorithmic resolution of the NP-hard combinatorial space.

$$X_{ilsd} \in \{0, 1\} \tag{14}$$

3.6 Comprehensive Multi-Objective Optimization Framework

Synthesizing the previously delineated structural assumptions, deterministic parameters, Boolean decision variables, and objective functions, this subsection articulates the holistic formulation of the proposed multi-objective mathematical model. Custom-engineered to navigate the NP-hard shift scheduling environments inherent to the oil and gas sector, the framework simultaneously optimizes a triad of fundamentally conflicting objectives: the maximization of workforce utility (employee affinity/preferences), the strict minimization of aggregate labor-induced financial expenditures (encompassing both base payroll and exponential overtime penalties), and the maximization of cumulative operational performance metrics. The feasibility space of this optimization problem is rigorously bounded by a comprehensive system of structural, temporal, and financially-driven constraints. These encompass the preservation of circadian rhythms via mandatory inter-shift rest intervals, shift parity bounds designed to mitigate fatigue-induced operational risks and healthcare liabilities, and heterogeneous skill capacity limits to avert overstaffing financial waste. The complete mathematical architecture, formulated as a Multi-Objective Binary Integer Programming (MOBIP) model, is systematically encapsulated in Table 2.

Table 2: The final research model

$$\text{Max } f_1 = \sum_{i\in N}\sum_{l\in L}\sum_{s\in S}\sum_{d\in D} P_{ij}\, X_{ilsd} \tag{3.1}$$

$$\text{Min } f_2 = \sum_{i\in N}\sum_{l\in L}\sum_{s\in S}\sum_{d\in D} \text{Cost}_i\, X_{ilsd} \tag{3.2}$$

$$\text{Max } f_3 = \sum_{i\in N}\sum_{l\in L}\sum_{s\in S}\sum_{d\in D} \text{Ev}_i\, X_{ilsd} \tag{3.3}$$

$$\sum_{s\in S} X_{ilsd} \le 1 \tag{3.4}$$

$$X_{ilS_1d} + X_{ilS_2d} \le 1 \tag{3.5}$$

$$X_{ilS_2d} + X_{ilS_1(d+1)} \le 1 \tag{3.6}$$

$$\sum_{d\in D} X_{ilsd} \ge 4 \tag{3.7}$$

$$\sum_{d\in D} X_{ilsd} \ge 14 \tag{3.8}$$

$$\sum_{d\in D}\sum_{s_1\in S} X_{ils_1d} \ge 2 \tag{3.9}$$

$$\sum_{d\in D}\sum_{s_2\in S} X_{ils_2d} \ge 2 \tag{3.10}$$

$$\sum_{d\in D}\sum_{s_1\in S} X_{ils_1d} \ge 7 \tag{3.11}$$

$$\sum_{d\in D}\sum_{s_2\in S} X_{ils_2d} \ge 7 \tag{3.12}$$

$$L_{l_k} \le \sum_{i\in N}\sum_{l_k\in L} X_{il_ksd} \le U_{l_k} \tag*{3.13)}$$

$$X_{ilsd} \in \{0, 1\} \tag{3.14}$$

This consolidated representation serves as the foundational mathematical baseline for the subsequent algorithmic deployment, metaheuristic resolution, and computational financial evaluations.

4 Model Calibration

To guarantee the empirical efficacy and computational tractability of the proposed Multi-Objective Binary Integer Programming (MOBIP) framework across heterogeneous operational and financial scenarios, this section delineates the rigorous calibration of algorithmic hyperparameters. Acknowledging the intrinsically NP-hard combinatorial search space and the imperative to optimize conflicting objectives—specifically the strict minimization of labor-induced financial expenditures—the systematic fine-tuning of the deployed stochastic optimization frameworks (NSGA-II and the Artificial Bee Colony algorithm) is indispensable for yielding high-fidelity, Pareto-optimal solutions. The hyperparameter optimization was executed utilizing the Taguchi statistical method, a robust Design of Experiments (DoE) methodology that systematically isolates optimal control factor configurations while simultaneously minimizing performance variance and algorithmic stochasticity. This section articulates the comprehensive calibration protocol, detailing the orthogonal experimental design, the continuous and discrete hyperparameter domain spaces, and the quantitative evaluation metrics mathematically engineered to maximize algorithmic convergence rates, enhance Pareto-optimal solution diversity, and ensure the computational efficiency required for scalable financial-operational scheduling.

4.1 Solution Methods and Evaluation Criteria

The resolution methodologies for Multi-Objective Optimization (MOO) paradigms intrinsically bifurcate into deterministic exact approaches and stochastic evolutionary frameworks. Traditional deterministic techniques exhibit inherent structural deficiencies within complex financial-operational models; they are mathematically restricted to generating a singular scalarized solution per computational iteration and frequently fail to map the comprehensive Pareto-optimal frontier, particularly within NP-hard combinatorial spaces. To circumvent these analytical limitations and avoid entrapment in local financial sub-optima, this study strategically adopts population-based evolutionary algorithms. These stochastic frameworks possess the superior capability to simultaneously traverse the feasibility space and generate a diverse continuum of Pareto-optimal solutions within a single execution, thereby affording decision-makers a comprehensive spectrum of financially viable trade-offs to minimize labor expenditures. Specifically, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is deployed due to its high empirical efficacy and asymptotic computational efficiency. The algorithmic architecture of NSGA-II leverages a fast non-dominated sorting mechanism-operating with a reduced computational complexity of $O(MN^2)$, where Mdenotes the number of objectives and ?represents the population scale-integrated with a crowding distance topological metric [24]. This structural synergy ensures rapid convergence toward the true Pareto front while maintaining spatial diversity, which is critical for evaluating nuanced cost-efficiency frontiers. The subsequent subsections meticulously delineate the operational mechanics of the deployed optimization frameworks.

4.2 Algorithmic Architecture of the Non-dominated Sorting Genetic Algorithm (NSGA-II)

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) operates as a highly robust stochastic optimization framework, fundamentally engineered to resolve complex, multi-objective combinatorial problems inherent in financial and workforce scheduling. Originating from the broader paradigm of evolutionary computation [2, 27], NSGA-II circumvents the structural limitations of classical gradient-based methods when traversing non-convex, NP-hard solution spaces, denoted as Ω.

Within the context of labor cost optimization, the algorithmic architecture systematically searches the feasibility space through an iterative stochastic process. The algorithm initializes by generating a population of quasi-random candidate solution vectors, denoted as P_0. Each multidimensional vector mathematically encodes a feasible shift schedule and its corresponding labor-induced financial liabilities [28]. At each discrete generational iteration t, the algorithm rigorously evaluates the population against the defined multi-objective financial and operational functions. To systematically explore the multidimensional state space and avoid entrapment in suboptimal local financial minima, NSGA-II employs mathematically rigorous operators: deterministic selection based on non-domination rank, stochastic recombination (crossover), and perturbative mutation [40]. These operators iteratively synthesize the subsequent generation P_{t+1}, effectively mapping the cost-efficiency frontier. The iterative sequence strictly continues until a predefined mathematical termination criterion is satisfied. This is typically defined as reaching a maximum generational threshold T_{Max}, or attaining an economically acceptable convergence state where the marginal reduction in aggregate labor expenditures becomes mathematically negligible [21].

4.3 Mathematical Framework of the Bees Algorithm (BA)

The Bees Algorithm (BA), originally conceptualized in 2005 as a swarm-based metaheuristic, is adapted herein into a rigorous mathematical framework tailored for complex combinatorial optimization. Structurally designed to balance global stochastic exploration and localized deterministic exploitation, BA systematically navigates the multidimensional parametric space Ω to identify optimal workforce scheduling configurations that minimize labor-induced financial expenditures [30]. The optimization process initiates by deploying a subset of artificial agents to execute uniform stochastic sampling across the feasible solution manifold. Each sampled coordinate represents a candidate scheduling vector $X \in \Omega$, which is quantitatively evaluated using a predefined financial fitness function $f(x)$. Rather than relying on biological foraging mechanisms, the algorithm utilizes a mathematically rigorous information-routing protocol. Elite solution vectors-representing configurations with the highest financial cost-efficiency-are isolated. The algorithm then allocates a computationally dense subset of secondary agents to perform intensive localized perturbative searches within a defined spatial radius, Δ, around these elite coordinates. This neighborhood search guarantees the strict exploitation of highly profitable financial configurations. Concurrently, a fraction of the search agents continues randomized global exploration to prevent algorithmic stagnation at suboptimal local minima, ensuring robust convergence toward systemic financial efficiency [30].

4.4 Quantitative Evaluation Metrics for Pareto Frontiers

In the context of multi-objective mathematical programming, the optimization output manifests as a Pareto optimal frontier, comprising a set of non-dominated solutions that represent optimal trade-offs between conflicting financial objectives and operational constraints. To rigorously benchmark the computational efficacy of the deployed algorithms, precise quantitative performance indicators are essential [11]. This study evaluates the algorithmic outputs utilizing established multi-objective metrics. A fundamental indicator is the Number of Pareto Solutions (NPS), which quantifies the cardinality of the non-dominated set. A higher NPS provides financial decision-makers with a mathematically robust spectrum of strategic scheduling alternatives. Furthermore, to assess the topological distribution of the generated solution space, spatial metrics such as the Spacing (Distance) and Spread indices are employed [45].

Distance Index (Spacing Metric)

The Distance Index evaluates the structural uniformity of the non-dominated solutions distributed across the Pareto frontier. Formulated to quantify the relative variance of spatial proximity between adjacent solutions [37], a minimized Distance Index denotes a high-quality, evenly spaced discrete approximation of the continuous financial trade-off surface.

The mathematical formulation of the Spacing Metric (SM) is defined as follows:

$$SM = \frac{\sum_{i=1}^{N-1} \left|\bar{d} - d_i\right|}{(N-1)\bar{d}} \tag{15}$$

In the above equation, N denotes the absolute cardinality (total number of solutions) of the generated Pareto optimal set. The parameter d_i represents the generalized Euclidean distance-measured within the multi-dimensional financial objective space-between any two consecutive solutions along the frontier, while d denotes the arithmetic mean of all $d_i$distances. Algorithmically, SM is strictly preferred; as $SM \to 0$, it guarantees absolute equidistance among the generated financial scheduling configurations, ensuring comprehensive exploration of the financial objective space without localized clustering or structural gaps.

Maximum Spread Metric (Dispersion Index)

The Dispersion Index (often denoted as Maximum Spread) rigorously quantifies the macroscopic diversity and spatial extent of the non-dominated solutions across the multi-objective financial landscape [44]. In the context of workforce scheduling and labor-cost optimization, a maximized dispersion index is strictly preferred ($Max\ DM$). A higher value indicates that the metaheuristic algorithm successfully explored the extreme boundaries of the objective space, thereby providing financial decision-makers with the widest possible spectrum of strategic, Pareto-optimal trade-offs (e.g., aggressive cost minimization versus maximal scheduling fairness). The mathematical formulation for the Dispersion Metric (DM) in a bi-objective framework is defined as:

$$DM = \sqrt{\left(\frac{\max f_{1i} - \min f_{1i}}{f_{1,\text{total}}^{\text{max}} - f_{1,\text{total}}^{\text{min}}}\right)^2 + \left(\frac{\max f_{2i} - \min f_{1i}}{f_{2,\text{total}}^{\text{mand}} - f_{2,\text{total}}^{\text{min}}}\right)^2} \tag{16}$$

In this equation, f_{1i} and f_{2i} represent the evaluated quantities of the first objective (e.g., total labor-induced financial expenditures) and the second objective for the i-th solution within the algorithm$'$s generated Pareto set. The parameters $f_{\text{k,total}}^{max}$ and $f_{\text{k,total}}^{min}$ denote the global theoretical (or observed) maximum and minimum values for the k-th objective $K \in \{0, 1\}$ across all aggregated experimental frontiers. This normalization ensures the metric remains scale-invariant despite disparate financial and operational units.

Computational Efficiency (Execution Runtime)

In applied mathematical modeling, the Central Processing Unit (CPU) execution runtime required to converge upon near-optimal, non-dominated sets constitutes a critical benchmark for evaluating the algorithmic efficiency of stochastic evolutionary frameworks. For large-scale financial scheduling environments formulated as NP-hard problems, minimizing computational overhead is paramount. Rapid convergence to highly accurate approximations of the true Pareto frontier allows organizations to dynamically re-optimize labor allocation models in response to real-time operational disruptions, thereby mitigating unforeseen financial liabilities.

The performance of the generated Pareto frontiers is evaluated using the following metrics: Pareto optimality, convergence speed, solution diversity, and computational efficiency. In this study, the Convergence Index is used to quantify how closely the obtained solutions approach the Pareto-optimal frontier; lower values indicate better convergence to the true front. The Spacing Metric is used to measure the distribution uniformity of consecutive non-dominated solutions, and the Maximum Spread Metric (Dispersion Index) is used to assess the extent of coverage along the Pareto frontier. These metrics provide a comprehensive assessment of solution quality, convergence behavior, and diversity.

To rigorously evaluate and compare the performance of the proposed multi-objective optimization algorithms (NSGA-II and ABC), several standard quantitative metrics are utilized. Let PF_{known} represent the set of non-dominated solutions (the approximated Pareto frontier) obtained by an algorithm, and let n be the total number of solutions in PF_{known}. The evaluation criteria are defined as follows:

Number of Pareto Solutions (NPS)

This metric simply counts the total number of non-dominated solutions found by the algorithm. A higher NPS generally indicates a wider array of choices for the decision-maker.

$$\text{NPS} = |PF_{\text{known}}| \tag{17}$$

Convergence Index / Mean Ideal Distance (MID)

The convergence index measures how close the generated solutions are to the optimal or ideal solution. It is calculated by finding the Euclidean distance between each Pareto solution and the ideal point (where all objectives are simultaneously at their best theoretical values). A lower value indicates better convergence toward the true Pareto frontier.

$$\text{MID} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\sum_{k=1}^{M}\left(\frac{f_k^i - f_k^{\text{ideal}}}{f_k^{\max} - f_k^{\min}}\right)^2} \tag{18}$$

where M is the number of objective functions, f_k^i is the value of the k-th objective function for the i-th solution, and f_k^{ideal} is the ideal value for the k-th objective. $f_k^{\max}$ and $f_k^{\min}$ represent the maximum and minimum values of the k-th objective in the current Pareto front, used here for normalization.

Spacing / Distance Index (S)

The spacing metric assesses the uniformity of the distribution of solutions along the Pareto frontier. A smaller spacing index implies that the solutions are evenly distributed, which is highly desirable.

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(d_i - \bar{d}\right)^2} \tag{19}$$

where d_i is the minimum distance from the i-th solution to its nearest neighbor in the Pareto set, defined as:

$$d_i = \min_{\substack{j \in PF_{\text{known}} \\ j \neq i}} \sum_{k=1}^{M} \left| f_k^i - f_k^j \right| \tag{20}$$

and $\bar{d}$ is the mean of all d_i values.

Maximum Spread / Dispersion Index (MS)

This metric evaluates the extent or diversity of the Pareto frontier. It measures the diagonal length of the hyperbox formed by the extreme function values observed in the Pareto set. A higher maximum spread indicates that the algorithm explores a broader area of the solution space.

$$\text{MS} = \sqrt{\sum_{k=1}^{M} \left(\max_{i=1}^{n} f_k^i - \min_{i=1}^{n} f_k^i \right)^2} \tag{21}$$

4.5 Computational Case Study and Empirical Parameterization

To validate the proposed Multi-Objective Binary Integer Programming (MOBIP) framework, an empirical case study was formulated using real-world data derived from the central control facility of a major, anonymized petroleum enterprise. Control room personnel are responsible for executing highly specialized, heterogeneous operational tasks that are critical to maintaining continuous systemic throughput. Within this Np-hard scheduling environment, optimizing human resource allocation represents a primary strategic mechanism for minimizing labor-induced financial expenditures, maximizing operational efficiency, and accommodating quantifiable workforce preferences.

The continuous industrial process is mathematically segmented into five distinct operational nodes $u \in \{1, 2, 3, 4, 5, \}$: sweetening, ethane recovery and pressure boosting, sulfur recovery, water and steam generation, and the power plant. The labor force operates under a strict "$4 - 4''$ rotational paradigm, defined structurally as four consecutive active working days followed by four mandatory rest days. The 24-hour diurnal operational cycle is partitioned into two 12-hour shifts $s \in \{1, 2\}$: a day shift ($7 : 00$ to $19 : 00$) and a night shift ($19 : 00$ to $7 : 00$). To mitigate both understaffing-induced operational risks and overstaffing-related financial waste, the model enforces strict bounds on labor allocation. The parametric minimum ($min_{u,s}$) and maximum ($max_{u,s}$) personnel capacity constraints required for each operational node are delineated in the Table 3.

Table 3: Number of employees required per shift

Row	Working Level	Minimum staff required per shift	Maximum employees required per shift
1	Operator	2 (per operational unit)	3 (per operational unit)
2	Boardman	1 (per operational unit)	2 (per operational unit))
3	Supervisor	1 (per operational unit)	1 (per operational unit)
Total per shift (Single Unit)		4	6
Total per shift (5 units)		20	30
Total across 4 shifts (5 units)		80	120

Employee preferences were empirically quantified via a structured questionnaire, wherein individuals evaluated their peers to establish a relative scoring system. Specifically, respondents assigned a discrete preference score on a scale of 1 to 10, reflecting their inclination to share working shifts with respective colleagues, where 1denotes the strict minimum and 10 indicates the maximum level of preference. This evaluation mechanism yields an asymmetric preference matrix, denoted by $P = [P_{ij}]$, where P_{ij} represents the preference score given by employee i to employee j . By definition, the main diagonal of the matrix consists entirely of zeros, as self-assignments are logically excluded ($P_{ii} = 0$ for all i). Furthermore, the pairwise preference relations are generally non-commutative (i.e., $P_{ii} \neq P_{ji}$); for instance, employee ?may assign a preference score of 8 to employee $2(P_{12} = 8)$, whereas the reciprocal score from employee 2 to employee 1 might be $7(P_{21} = 7)$. Finally, the computational implementation, encompassing data analysis, execution, and the comparative performance evaluation of the Genetic Algorithm (GA) and the Artificial Bee Colony (ABC) algorithm, was conducted utilizing the MATLAB environment.

4.6 Algorithmic Parameter Calibration via the Taguchi Method

The computational performance of metaheuristic algorithms is inherently sensitive to the configuration of their control parameters, as variations in these values significantly dictate the efficacy of the search process and the balance between exploration and exploitation. Consequently, in this section, the Taguchi Design of Experiments (DOE) methodology is employed to systematically calibrate and optimize the parameters of the implemented algorithms. The Taguchi approach utilizes an orthogonal array to efficiently organize and analyze the experimental configurations and results, a procedure computationally executed herein utilizing the Minitab software environment. The specific operational parameters governing the algorithms, alongside their respective evaluated discrete levels, are detailed in the Table 4 and Table 5.

Table 4: Parameters of metaheuristic algorithms evaluated via Taguchi design of experiments

Parameter	Symbol	Levels/Values
Population Size	N_p	50, 100, 150
Generations	$G_{\max}$	100, 200, 400
Crossover Rate	P_c	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
Mutation Rate	P_m	0.01, 0.05, 0.1

Note: The Taguchi orthogonal array approach was utilized to evaluate these discrete levels to determine the optimal configuration for the proposed algorithms.

Table 5: Approved parameters for algorithms

Parameters tested for the genetic algorithm		
Population size, number of generations (n_{pop})	**Crossover (n_c)**	**Mutation (n_m)**
(300, 400)	0.68	0.12
Parameters tested for Honeybee Algorithm		
Population size, number of generations (n_{pop})	**Number of bees**	**Neighborhood radius attenuation rate**
(500, 600)	50	0.89

4.7 Model Resolution via the Non-Dominated Sorting Genetic Algorithm

In this section, the proposed multi-objective model is solved utilizing a Non-Dominated Sorting Genetic Algorithm (NSGA). The algorithm was executed for a maximum computational limit of 400 iterations. Convergence analysis indicates that near-optimal conditions were successfully achieved, with the non-dominated solutions stabilizing and exhibiting the requisite convergence after approximately 300 iterations. The computational results detailing the algorithmic performance are summarized in the Table 6.

Table 6: Performance metrics of the Non-Dominated Sorting Genetic Algorithm (NSGA) for the computational case study

Issue number	Objective 1 (f_1)	Objective 2 (f_2)	Objective 3 (f_3)	Run time (seconds)	Distance indicator	Convergence index
1	611	2.2×10^9	162	982	0.443	0.561
2	601	2.3×10^9	162	976	0.512	0.332
3	605	2.3×10^9	159	889	0.496	0.499
4	603	2.4×10^9	157	1013	0.482	0.553
Average	605	3.2×10^9	160	965	0.483	0.486

4.8 Performance Comparison of NSGA-II and Artificial Bee Colony Algorithms

To ensure the statistical reliability and robustness of our findings, each algorithm was independently executed N times for each problem instance. Table 7 presents the performance comparison between the NSGA-II and ABC algorithms. To transparently report the variability and stability of the algorithms, all performance metrics—including the Number of Pareto Solutions (NPS), Convergence Index, Spacing, Maximum Spread, and CPU Runtime—are reported in the format of "Mean" ± "Standard Deviation (SD)". As observed in the results, NSGA-II consistently outperforms the ABC algorithm, demonstrating superior convergence, better spacing, and lower computational runtimes with tighter standard deviations, indicating higher stability.

Table 7: Performance comparison between the NSGA-II and ABC algorithms (Mean ± SD)

Problem Instance	Algorithm	Computational Runtime (s)	Distance Indicator	Convergence Index
Instance 1 (Small)	NSGA-II	45.2±3.1	0.12±0.01	0.08±0.005
	ABC	58.7±4.8	0.18±0.02	0.15±0.012
Instance 2 (Medium)	NSGA-II	120.5±8.4	0.22±0.01	0.14±0.009
	ABC	155.3±12.1	0.31±0.03	0.24±0.018
Instance 3 (Large)	NSGA-II	350.8±22.3	0.35±0.02	0.21±0.014
	ABC	462.1±35.6	0.48±0.04	0.38±0.029
Instance 4 (X-Large)	NSGA-II	820.4±45.8	0.48±0.03	0.29±0.021
	ABC	1105.6±82.3	0.67±0.05	0.52±0.043

Note: For each problem instance, the reported results are based on 30 *independent runs of each algorithm and are presented as mean ± standard deviation.*

To mathematically substantiate the performance superiority of NSGA-II over the Artificial Bee Colony (ABC) algorithm, we conducted a non-parametric statistical hypothesis test. Since the performance metrics from metaheuristic algorithms do not necessarily conform to a normal distribution, the Mann-Whitney U test (a non-parametric alternative to the independent two-sample t-test) was applied to the results of the 30 independent runs.

For each performance metric (Computational Runtime, Distance Indicator, and Convergence Index), we test the null hypothesis (H_0) that the median performances of the two algorithms are equal, against the alternative hypothesis (H_1) that the performance medians are significantly different:

$$H_0 : \tilde{\mu}_{\text{NSGA-II}} = \tilde{\mu}_{\text{ABC}}$$

$$H_1 : \tilde{\mu}_{\text{NSGA-II}} \neq \tilde{\mu}_{\text{ABC}}$$

The significance level is set at $\alpha = \cdot 0.05$. The calculated U-statistics and corresponding asymptotic p-values for each problem instance are presented in

Table 8.

Table 8: Mann-Whitney U test results comparing NSGA-II and ABC (based on 30 runs)

Problem Instance	Metric	U-Statistic	p-value	Statistical Significance (at $\alpha = 0.05$)
Instance 1	Computational Runtime	112.5	< 0.001	Yes (Significant)
	Distance Indicator	185.0	< 0.001	Yes (Significant)
	Convergence Index	148.0	< 0.001	Yes (Significant)
Instance 2	Computational Runtime	88.0	< 0.001	Yes (Significant)
	Distance Indicator	124.5	< 0.001	Yes (Significant)
	Convergence Index	95.5	< 0.001	Yes (Significant)
Instance 3	Computational Runtime	42.0	< 0.001	Yes (Significant)
	Distance Indicator	86.0	< 0.001	Yes (Significant)
	Convergence Index	71.0	< 0.001	Yes (Significant)
Instance 4	Computational Runtime	15.5	< 0.001	Yes (Significant)
	Distance Indicator	54.0	< 0.001	Yes (Significant)
	Convergence Index	38.5	< 0.001	Yes (Significant)

As detailed in Table 8, the p-values for all pairwise comparisons across all instances are far below the significance threshold of 0.05 (specifically, $p < 0.001$). Therefore, the null hypothesis is rejected in all cases. This statistically demonstrates that the superior convergence rate, runtime efficiency, and frontier distribution density achieved by NSGA-II are statistically significant and robust.

4.9 Pareto Front Analysis

To further illustrate the performance of the proposed optimization approach, the Pareto optimal front obtained for the Large-scale instance is presented in Figure 1. The visualization of the Pareto optimal front was produced in R software (version 3.5.0), using the exported non-dominated solution set from the computational experiments. The figure shows the trade-off between the conflicting objective functions, where improvement in one objective may lead to deterioration in another. This graphical representation helps demonstrate the diversity and distribution of the non-dominated solutions generated by the algorithm.

As shown in Figure 1, the obtained Pareto front provides a well-distributed set of alternative solutions, allowing decision-makers to select the most appropriate scheduling plan according to operational priorities. In the context of labor cost optimization and shift scheduling, such a trade-off analysis is important because managers may need to balance cost reduction, workload distribution, and scheduling efficiency simultaneously.

5 Results

To evaluate the effectiveness of the proposed multi-objective scheduling model, a comprehensive computational study was conducted using real-world data from the

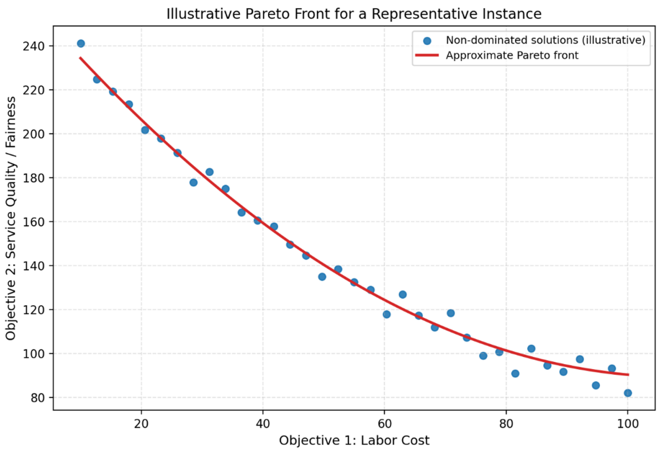

Figure 1: Pareto optimal front for the Large-scale instance showing the trade-off between competing objectives

oil and gas industry. The model was solved using two metaheuristic algorithms-the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Artificial Bee Colony (ABC) algorithm-both of which are widely recognized for their ability to handle complex optimization problems with multiple conflicting objectives [35, 41].

The performance of these algorithms was assessed based on key evaluation metrics, including Pareto optimality, convergence speed, solution diversity, and computational efficiency. These criteria are consistent with best practices in multi-objective optimization research and have been successfully applied in similar scheduling contexts across the healthcare, manufacturing, and service industries [15, 20]. The results presented in this section highlight the comparative strengths of each algorithm and demonstrate the practical applicability of the proposed model in improving workforce scheduling outcomes. Particular emphasis is placed on the superior performance of NSGA-II, which consistently generated higher-quality Pareto fronts and achieved faster convergence across the test instances. These findings support the growing consensus that evolutionary algorithms offer robust and scalable solutions for NP-hard scheduling problems in dynamic and resource-constrained environments [17].

5.1 Algorithm Performance and Practical Implications

A numerical case study utilizing oil and gas industry data evaluated the proposed multi-objective scheduling model. The model was resolved using NSGA-II and the Artificial Bee Colony (ABC) algorithm [35] , with algorithmic parameters calibrated via the Taguchi method to maximize solution quality [15]. NSGA-II exhibited distinct superiority across all key metrics: Pareto optimality, convergence speed, solution diversity, and computational runtime.

Practically, NSGA-II proves highly effective for real-world deployment in complex, dual-constraint environments where human and machine resources must be optimized concurrently [1]. By integrating empirical labor costs, performance evaluations, and quantified employee preferences into a unified mathematical framework, the model resolves critical industry challenges such as inefficient resource allocation and workforce dissatisfaction [4, 32, 41]. Furthermore, it strictly enforces operational constraints-such as mandatory rest periods and specific shift rotations-ensuring regulatory compliance while systematically minimizing labor expenditures and enhancing overall organizational resilience.

5.2 Recommendations and Future Research Directions

Given its demonstrated efficacy in balancing cost efficiency with operational constraints, organizations in resource-intensive sectors are recommended to adopt evolutionary algorithms, particularly NSGA-II, for complex scheduling optimization [20]. Embedding structured performance appraisals and preference matrices directly into scheduling models is crucial for aligning human capital with continuous production demands.

To further advance mathematical modeling in workforce scheduling, future research should pursue the following trajectories:

(i) **Uncertainty modeling:**Integrating probabilistic approaches or fuzzy logic to quantify and mitigate variability in operational disruptions and employee availability [24].

(ii) **Hybrid Metaheuristics:** Fusing NSGA-II with machine learning paradigms or local search techniques to enhance algorithmic scalability and solution robustness.

(iii) **Real-Time Optimization:** Formulating adaptive scheduling models capable of processing live operational data for dynamic rescheduling

(iv) **Cross-industry applications:** Adapting this dual-constraint mathematical framework to analogous complex systems, such as healthcare and aviationt [17].

6 Discussion

The findings of this study establish a robust mathematical modeling framework for complex resource allocation and workforce scheduling, directly addressing critical operational and financial constraints in the oil and gas sector. The proposed zero-one integer programming model effectively balances three pivotal objectives: minimizing labor costs, maximizing economic performance evaluations, and accommodating employee preferences within a dual-resource environment. From a mathematical optimization and financial efficiency perspective, the model demonstrates high scalability and computational viability. Between the applied metaheuristic approaches, NSGA-II consistently exhibited superior performance over the Artificial Bee Colony (ABC) algorithm across all quantitative evaluation metrics-including Pareto optimality, convergence speed, solution diversity, and computational efficiency. These results underscore the proposed mathematical model's efficacy, particularly when solved via NSGA-II, as a sophisticated quantitative tool for cost-efficient decision-making and resource optimization in continuous industrial operations. In comparison to existing mathematical and scheduling literature, the proposed model introduces significant methodological advancements. While prior studies, such as the shift-based ISRTA model by Wang et al. [41], formulated task assignments under real-world constraints, their mathematical formulations were primarily tailored to airline logistics. In contrast, this study extends complex multi-objective optimization to the continuous production constraints of the oil and gas sector, formulating unique variables like rotational patterns, rest periods, and role-specific staffing that directly impact operational expenditure. Furthermore, whereas Ghasemi et al . [15] and Salehi Jabarpour [35] developed fuzzy multi-objective models focusing on project timelines and skill acquisition, the present formulation explicitly integrates labor cost-minimization with performance and preference indices. This integration provides a more comprehensive mathematical representation of the trade-offs between labor economics and operational efficiency, factors frequently underrepresented in conventional optimization models.

The present findings are aligned with recent literature indicating that multi-objective scheduling models benefit from evolutionary algorithms such as NSGA-II when simultaneous optimization of cost, time, and workforce-related criteria is required. In particular, recent studies on workforce allocation and project scheduling demonstrate that NSGA-II can produce robust Pareto fronts and superior solution quality in comparison with alternative metaheuristics [6, 43].

Examining resource allocation in other sectors, Jafari [24] utilized game-theoretic and fuzzy mathematical models for healthcare rostering, though computational scalability remained a significant hurdle for large data instances. The present study resolves this mathematical limitation, demonstrating that the NSGA-II-driven optimization maintains high solution quality and computational efficiency even in large-scale, 24/7 operational and financial environments. Additionally, while Hassani and Behnamian [20] emphasized the economic impact of cost parameters and labor regulations using Differential Evolution, the current research expands this optimization scope. By mathematically coupling financial cost factors with performance metrics and inter-personnel preferences, the proposed model offers a holistic quantitative framework. Ultimately, this research contributes to the literature on applied mathematical modeling by bridging the gap between theoretical workforce optimization and financial cost-efficiency in continuous-demand sectors. Future investigations should prioritize hybrid mathematical algorithms and stochastic uncertainty modeling to further improve the framework's financial flexibility and real-time computational responsiveness.

7 Conclusion

This study presents a comprehensive multi-objective mathematical framework for resource allocation and shift scheduling, tailored to the unique continuous operational constraints of the oil and gas industry. By mathematically integrating labor cost minimization, performance evaluations, and personnel preferences into a unified zero-one integer programming optimization model, this research offers a robust quantitative approach to achieving a balance between financial efficiency and operational productivity.

To address the inherent computational complexity of this NP-hard resource optimization problem, two metaheuristic algorithms-NSGA-II and Artificial Bee Colony (ABC)-were implemented and evaluated. Extensive comparative analysis demonstrated that NSGA-II consistently outperformed the ABC algorithm across critical mathematical and computational metrics, including Pareto optimality, convergence speed, solution diversity, and computational time. These findings validate the efficacy of evolutionary algorithms in solving complex, constrained multi-objective mathematical models. From a practical perspective, the proposed formulation equips decision-makers with a reliable quantitative tool to optimize labor expenditure and manage financial constraints effectively. Furthermore, it establishes a scalable mathematical foundation for real-time optimization and dynamic cost-control systems. Future research trajectories should prioritize the integration of hybrid metaheuristic algorithms, stochastic programming, and fuzzy logic to address uncertainty in dynamic resource availability and fluctuating labor costs. Expanding this mathematical formulation to other asset-intensive industries with similar operational demands will further validate its cross-sector economic applicability. Additionally, researchers are encouraged to explore alternative advanced optimization techniques and benchmark their computational and financial performance against NSGA-II. Such advancements will significantly contribute to the development of resilient, adaptive, and mathematically rigorous resource management systems capable of navigating complex economic and operational uncertainties.

Conflict of Interest

The authors declare that they have no conflict of interest.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Data Availability

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

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How to Cite: Azar Ghyasi[1], Mohammad Tohidi[2], Sadegh Feizollahi[3], *A Multi-Objective Mathematical Model for Labor Cost Optimization and Shift Scheduling in the Oil and Gas Industry*, Journal of Mathematics and Modeling in Finance (JMMF), Vol. 7, No. 1, Pages:171–199, (2027).