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A BERT and NSGA-II Based Model for Workforce Resource Allocation Optimization in the Operational Stage of Commercial Buildings

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Abstract

Existing experience-based methods cannot effectively assist commercial building operators in allocating workforce resources according to contracts and balance multiple workforce management objectives under resource constraints, leading to misaligned allocation strategies. To address this issue, this study develops a workforce resource allocation optimization model based on BERT and the NSGA-II. First, a natural language processing (NLP) model is trained to extract operational tasks from contracts and match required workforce types, thereby establishing the framework for workforce allocation schemes. Second, a mathematical optimization model for workforce allocation strategies is constructed with the objectives of minimizing workforce wage costs (B1), maximizing average service levels (B2), and maximizing average digital technology acceptance (B3). An algorithm based on NSGA-II is then designed to solve the model and obtain the optimal Pareto solution set of allocation schemes. Third, the CRITIC–VIKOR method evaluates the Pareto set and determines the final recommended schemes. A case study was conducted on a university campus in Shandong, China, to validate the model's effectiveness. The results show that the NLP model successfully identified 14 operational tasks and 13 required workforce types from the contract. Compared with the operator's expected values (B1 = 46,0000 CNY, B2 = 65 points, B3 = 50 points), the optimal allocation scheme calculated using NSGA-II and the CRITIC–VIKOR method reduces B1 by 10.79%, increases B2 by 18.02%, and improves the B3 by 16.79%. This study formulates the workforce allocation problem in the operation stage as a mathematical optimization model and, for the first time, incorporates the workforce's digital technology acceptance as an optimization objective, thereby filling a theoretical gap in workforce management for commercial building operations. The proposed model provides operators with a semi-automated decision-support tool to enhance workforce management, thereby promoting the sustainable operation of commercial buildings.



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Keywords: commercial buildings; operation management; workforce management; multi-objective optimisation; NLP; NSGA-II

1. Introduction

The operation of commercial buildings constitutes a critical stage in the building life cycle, accounting for more than 80% of its duration and costs [1]. Compared with residential buildings, commercial buildings typically feature larger spatial scales, more diverse functional zones, higher technological complexity, and stricter service-level requirements [1,2]. With the continuous advancement of urbanization, the demand for commercial spaces

has grown rapidly, driving the expansion of building scale and functional complexity [3], making Operation and Maintenance (O&M) work ever more significant [4]. Recent studies have highlighted that efficient operational management ensures the safe and stable functioning of building systems [2,4–7], and directly affects key performance indicators during operation, including owner satisfaction [5], energy consumption [2,8], and cost control [6]. To reduce management burdens, building owners commonly delegate daily O&M tasks to professional property management companies through contractual arrangements [9].

However, according to the operation contracts signed between owners and operators, commercial building operations involve a wide range of task types [7], including cleaning, security, device maintenance, and customer services. These tasks differ significantly in their requirements for workforce skills, qualifications, and service capabilities. In practical operations, how to reasonably allocate workforce under limited resources [10,11]—so that allocation strategies can simultaneously meet multi-objectives such as contractual requirements, reduce workforce costs, and enhance the overall service capability of the workforce—constitutes one of the core challenges in management optimization for operators.

In practice, operators often manage workforce resource allocation during the operational stage of commercial buildings based on empirical methods [10,12]. However, this decision-making approach has three significant shortcomings: (1) it fails to fully utilize the detailed provisions in operation contracts, resulting in allocation strategies with low adaptability to the individualized needs of building operation [12]; (2) it lacks systematic multi-objective optimization models, making it challenging to balance objectives such as cost control and service quality; and (3) it does not consider the digital technology acceptance capability of workforce within the allocation constraints [13]. Insufficient digital acceptance prevents digital tools from functioning effectively in the context of digitalized OM of commercial buildings [14], thereby reducing service responsiveness and hindering the overall level of digital management. These issues lead to misaligned workforce allocation strategies, causing building operations to fall short of contract objectives. Recent advances in NLP technologies have provided new opportunities for digitization and intelligent operation management [12]. In particular, task extraction methods based on pre-trained language models (e.g., BERT) [15] can automatically identify operational tasks from project contracts and match them with the required types of workforce. Building on this, integrating multi-objective optimization algorithms enables the development of project-specific workforce allocation optimization strategies [16], thereby providing effective support for operators' workforce allocation decisions.

Against this background, this study proposes a workforce resource allocation optimization model for the operational stage of commercial buildings that integrates natural language processing and multi-objective optimization algorithm. The main work is as follows. First, a BERT-based NLP model is trained to automatically identify operation tasks in contracts and match them with the required workforce skill categories, thereby establishing the framework for workforce allocation schemes. Second, a mathematical optimization model for workforce allocation is constructed with the objectives of minimizing total workforce costs, maximizing average service levels, and maximizing average digital technology acceptance. An optimization algorithm based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is then designed to solve the model and generate a Pareto solution set of allocation schemes. Third, the CRITIC method is applied to compute the weights of the three objectives in the Pareto solution set, and the VIKOR method is used to evaluate and rank the Pareto solutions, selecting the optimal allocation scheme from the set. Finally, the proposed model is applied to workforce allocation decisions for the operation team of a newly established university campus in Shandong Province, China, verifying its effectiveness. The main contributions are as follows:

- (1) A mathematical optimization model for workforce allocation strategies is proposed, targeting workforce wage cost, service level, and digital technology acceptance. This model fills a research gap in workforce allocation during the operational stage of commercial buildings and, for the first time, incorporates workforce digital technology acceptance into the building sector's workforce allocation problem.
- (2) The optimization model integrating BERT, NSGA-II, and the CRITIC–VIKOR method realizes a semi-automated decision process of “demand identification-allocation optimization-optimal scheme selection.” It provides a practical decision support tool for commercial building operators to improve workforce management, thereby promoting the sustainable operation of commercial buildings.

The remainder of this study is structured as follows. Section 2 reviews the relevant literature. Section 3 details the methodology, including constructing and training the BERT-based NLP model, developing the mathematical model for workforce allocation optimization, designing the NSGA-II solution algorithm, and introducing the CRITIC–VIKOR evaluation method. Section 4 presents the case study, and Sections 5 and 6 provide the discussion and conclusion, respectively.

2. Literature Review

2.1. Current Research on Workforce Resource Allocation in Commercial Buildings

To address the misaligned workforce allocation strategies resulting from reliance on empirical methods [10,12], a growing body of research on workforce resource allocation in commercial buildings has emerged in recent years, which can be divided into two aspects: the construction stage and the operational stage.

(1) Construction Stage

Research on workforce allocation in the construction stage has undergone long-term development, resulting in a well-established body of theories and methods. Early studies primarily employed forecasting algorithms or regression models to formulate allocation strategies that met single workforce demands [17]. For instance, Florez et al. [18] developed a mixed-integer programming model for masonry construction that links worker attributes to site conditions, thereby optimizing crew formation. Similarly, Rabiei, H [19] proposed a multi-objective decision-making system that integrates MDCD, BWM, and TOPSIS to align stakeholder utilities, productivity requirements, and site conditions, enabling optimized worker assignment and crew formation in real construction environments. With the introduction of interdisciplinary theories, scholars have incorporated organizational behavior [20] and psychological factors [21] into decision-making, utilizing multi-objective optimization to design allocation schemes that balance workforce demand with individual needs, such as social interaction and career development. Additionally, some studies have approached the issue from the perspective of project portfolios, aiming to coordinate workforce allocation across multiple concurrent projects [22]. Wang et al. [17] developed a workforce allocation model for the COVID-19 pandemic that considers project prioritization, worker energy levels, and regional epidemic conditions. Then they employed a cellular automaton (CA) approach to simulate allocation strategies that support workforce allocation during work resumption.

(2) Operational Stage

Compared with the construction stage, research on workforce allocation during the operational stage of commercial buildings remains limited. Existing studies primarily focus on periodic maintenance and renovation tasks. For example, Cao et al. employed machine learning techniques to predict workforce demand for maintenance tasks in commercial buildings in Hong Kong [4]. Meanwhile, Yunjeong Mo et al. [12] developed an

NLP-based classification model to identify the required labor types from maintenance work orders automatically. However, explicit optimization models for daily operational tasks are still lacking. In commercial building operations, owners and operators define their responsibilities and service standards through operational contracts [9]. Within this contractual framework, operational tasks are characterized by diversity and high specialization, encompassing areas such as environmental maintenance, security services, facility management, and digital services. To ensure efficient task execution, operators must allocate different workforce resources according to task requirements [7]. Furthermore, unlike the construction stage, which emphasizes progress-driven task demands [23], the operation stage prioritizes long-term stability, requiring the continuous provision of reliable services and maintenance to guarantee the building's normal functioning throughout its life cycle. Consequently, allocating workforce resources to achieve contract objectives steadily has become a pressing optimization challenge under resource constraints.

To address this, this study employs NLP techniques to automatically identify workforce requirements from operational contracts, followed by multi-objective optimization to generate optimal allocation schemes under resource constraints. In doing so, it establishes an integrated workforce allocation optimization model that realizes “demand identification-allocation optimization-optimal scheme selection,” thereby filling the research gap in workforce allocation during the operational stage of commercial buildings.

2.2. Research on Workforce Digital Technology Acceptance

With the rapid advancement of digital technologies, operators across industries are actively exploring their applications in management and services to enhance operational efficiency and decision-making [24,25]. However, existing studies indicate that realizing expected benefits from digital technologies depends not only on the technologies' maturity but also, to a large extent, on workforce understanding and ability to apply relevant tools and systems [13,26]. This perspective is highly consistent with the core assumptions of the Technology Acceptance Model (TAM). TAM posits that individuals' adoption of new technologies is primarily influenced by perceived usefulness and ease of use, which shape their attitudes and behavioral intentions toward usage, ultimately affecting the actual implementation outcomes within organizations [27]. Based on this recognition, extensive research has been conducted in fields such as hospitality [28], healthcare [29], and education [30], aiming to reveal the impact mechanism of workforce digital technology acceptance on service quality. In the construction industry, related studies have also highlighted workforce digital technology acceptance as a critical factor influencing the successful implementation of digital technologies [13].

Nevertheless, how to systematically incorporate this factor into workforce allocation decisions during the operational stage remains an evident research gap. To address this, this study, drawing on the theoretical foundation of TAM [27], defines digital technology acceptance as the comprehensive reflection of workforce understanding, recognition, and ability to apply emerging digital tools and systems in the workplace. On this basis, it is incorporated as one of the optimization objectives in the workforce allocation model, ensuring that workforce strategies balance cost control and service quality while facilitating the effective adoption of digital technologies in practice.

3. Methods and Materials

The methodological framework was derived directly from the structure of the workforce allocation problem in commercial building operations. Operational tasks are defined explicitly in the contract, making task identification a necessary first step [12]. The identified tasks determine the required workforce types, quantities, and associated constraints.

Under limited resources, operators must satisfy these requirements while simultaneously improving various attributes of the allocation scheme (i.e., optimization objectives), which naturally leads to the formulation of a multi-objective allocation model [16,19]. Solving this model yields a set of Pareto-optimal schemes, which requires a subsequent decision-making procedure to determine the final allocation scheme [31]. Therefore, the methodological framework involves three sequential steps, as shown in Figure 1:

- (1) Training a BERT-based NLP model to identify workforce demand types from operation contracts;
- (2) Constructing the mathematical model for workforce allocation optimization and designing the NSGA-II algorithm to solve it;
- (3) Using the CRITIC–VIKOR method to evaluate the Pareto solution set and select the optimal allocation scheme.

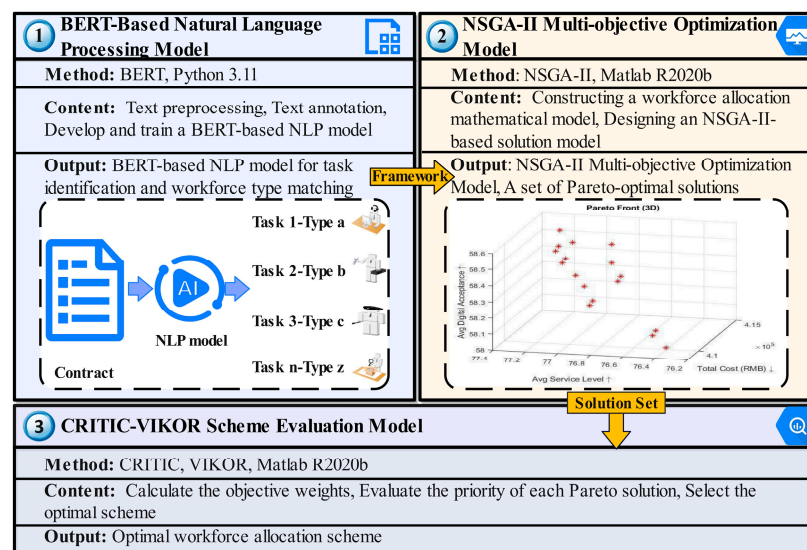


Figure 1. The methodological framework.

In summary, the proposed methodological framework realizes a semi-automated decision-making process composed of “demand identification—allocation optimization—scheme selection,” providing a systematic, actionable, and practically applicable decision-support method for workforce allocation during the operation phase.

3.1. BERT-Based Natural Language Processing Model

Commercial buildings are defined as non-residential facilities, including offices, industrial premises, hotels, schools, and hospitals [1,10,32]. The daily O&M tasks of these buildings vary considerably. To fully leverage the provisions in operation contracts and generate allocation strategies that accommodate the individualized operational needs of commercial buildings, this study designs an artificial intelligence model based on NLP. The model assists operators by automatically identifying operational tasks from contract contents and matching them with the corresponding workforce types.

3.1.1. BERT Model

In this study, workforce type matching is formulated as a multi-label classification task. BERT (Bidirectional Encoder Representations from Transformers), with its bidirectional Transformer architecture, effectively captures contextual semantic relationships [15,33] and is thus well suited for parsing and classifying complex contractual texts. Compared with models such as BiLSTM or CNN, BERT’s large-scale pre-training provides strong

transferability [34,35], ensuring robustness and generalization even with limited contract text data. Therefore, BERT is adopted as the NLP model in this research.

3.1.2. Dataset and Data Processing

The corpus required for model pre-training is collected from various commercial building operation contracts (e.g., the University of California, Merced campus operation agreement [36]). To improve the efficiency of model training and processing, the texts in the dataset are subjected to the following procedures: (1) Text processing. Optical Character Recognition (OCR) is applied to convert the original PDF files into TXT format, then remove non-operational content in the contracts. (2) Text cleaning. Irrelevant numbers, location names, and punctuation are deleted from the contracts, while the remaining text is converted to lowercase and stop words are removed. (3) Text augmentation. The sentence-segmented contract texts are reorganized to expand the sample size of the dataset.

(4) Text annotation. Based on existing research on commercial building operations [10,12] and the collected contract texts, an initial set of workforce category labels was designed. Next, operational management experts and managers from commercial buildings [37] were invited to evaluate and refine the classification labels, resulting in the workforce categories presented in Table 1. The processed contract texts were then annotated with multiple labels using the Doccano platform. Finally, 14 operation contracts of commercial buildings were cleaned and annotated, yielding a dataset of 4381 sentences.

Table 1. Workforce classification labels and codes.

Codes	Labels	Codes	Labels
T1	Cleaning personnel	T8	Metal worker
T2	Security personnel	T9	Mason
T3	Electrician	T10	Laborer
T4	Plumber	T11	Customer service personnel
T5	Carpenter	T12	Information systems administrator
T6	Painter	T13	Fire management personnel
T7	HVAC system technician	T14	Elevator service specialist

3.1.3. Model Setup

The training of the NLP model was implemented in Python 3.11, with the details as follows:

- (1) Data input. Based on BERT's special tokens, such as the sentence-start token [CLS] and the separator token [SEP] [34], the raw input was converted into sentence embedding vectors with a fixed length of 100.
- (2) Model parameters. The BERT model used for training consisted of 12 encoder units within the Transformer architecture and a 768-dimensional hidden layer. A dropout layer with a dropout rate of 0.1 was applied, and the batch size was set to 32. The multi-classification head produced 14 outputs, corresponding to 14 workforce category labels. The AdamW optimiser was employed with a learning rate of 0.001 [34]. The annotated dataset was randomly split into training and validation sets at a ratio of 7:3.
- (3) Evaluation metrics. The commonly used metrics for classification tasks—accuracy, precision, recall, and F1-score—were adopted [34,38]. These metrics were computed during training using the sklearn library.

3.1.4. Training Results

After completing the training iterations, the model was saved, and the results were output. According to the predefined evaluation metrics, the final performance achieved was: Accuracy = 0.79, Precision = 0.79, Recall = 0.80, and F1-score = 0.78.

3.1.5. Models Comparison

To further demonstrate the effectiveness and superiority of the proposed BERT-based NLP model in multi-label classification of operational tasks from commercial building contracts, a series of comparative experiments was conducted using several widely adopted machine learning and deep learning models. These baseline models cover three major categories: traditional machine learning methods, classical deep learning architectures, and lightweight pre-trained language models. All baseline models were trained and evaluated on the same annotated dataset described in Section 3.1.2, ensuring a fair comparison. In addition, to verify the performance of the proposed model, hyperparameter tuning was conducted during the training of all baseline models to ensure that each model achieved its optimal performance. The specific tuned parameters are presented in Table S1.

Table 2 summarizes the performance of all baseline models compared to the proposed BERT model. The results indicate that traditional machine learning methods yielded the lowest performance due to their inability to capture contextual semantics. Deep learning models (TextCNN and BiLSTM) achieved moderate improvements but remained inferior to pre-trained models. DistilBERT outperformed all non-pretrained models, demonstrating the value of transfer learning.

Table 2. Model training results.

Model	Accuracy	Precision	Recall	F1-Score
TF-IDF + LR	0.56	0.52	0.48	0.49
TF-IDF + SVM	0.61	0.58	0.55	0.56
Random Forest	0.54	0.50	0.47	0.48
TextCNN	0.65	0.63	0.59	0.61
BiLSTM	0.67	0.64	0.62	0.63
DistilBERT	0.74	0.73	0.72	0.72
Proposed model	0.79	0.79	0.80	0.78

The proposed BERT-based NLP model significantly outperformed all baseline methods across every evaluation metric. This confirms that BERT's bidirectional contextual representations and large-scale pre-training are particularly well-suited for the classification tasks involving complex contract texts in this study.

3.2. Mathematical Programming Model

3.2.1. Problem Description

This study's multi-objective optimization problem of workforce allocation is described as follows. Suppose a commercial building project is about to begin operation. Based on the identification results of the NLP model, the operation process consists of l daily operational tasks, each requiring employees with specific skills and involving a total of t skill types. According to the characteristics of commercial building operation tasks, these tasks are categorized by frequency into 24 h [37], daily [39], periodic [10], and emergency tasks [40,41], each with distinct rules for calculating workforce demands. This rule system centers on the quantitative estimation of total task workload and the per capita workforce load [42–44], providing a systematic basis for deriving the required workforce size for various operational tasks.

(1) 24 h tasks:

$$N_{ho} = \sum_z P_z \frac{24}{L_z} (1 + O) \quad (1)$$

Here, N_{ho} denotes the workforce number for 24 h tasks, P_z denotes the number of personnel required to be on duty simultaneously at the same location, L_z denotes the duration of a single shift, O denotes the redundancy coefficient.

(2) Daily tasks:

$$N_{da} = \sum_k \frac{S_k}{L_k} (1 + O) \quad (2)$$

Here, N_{da} denotes the number of workforce required for daily tasks, O is the redundancy coefficient, S_k is the work area of region k , and L_k denotes the unit workforce load.

(3) Periodic tasks:

$$N_{pm} = \sum_m \frac{S_m f_m}{L_m} (1 + O) \quad (3)$$

$$N_{po} = \sum_o \frac{S_o f_o}{L_o} (1 + O) \quad (4)$$

In this study, the calculation of workforce demand for periodic tasks is divided into two categories: calculations based on work-area rules (N_{pm}) and calculations based on the number of equipment items (N_{po}).

Here, S_m represents the work area that requires maintenance. f_m represents the monthly maintenance workload for the unit area. L_m represents the workload of a single unit of workforce. S_o denotes the number of pieces of equipment that require maintenance, f_o represents the monthly maintenance workload for each piece of equipment. L_o represents the workload of a single unit of workforce. O denotes the redundancy coefficient.

(4) Emergency tasks

$$N_{em} = \frac{\omega \rho s}{L_e} \quad (5)$$

where N_{em} denotes the workforce demand for emergency tasks, where $\omega \rho$ is the monthly number of emergency events and s is the average handling time. L_e represents the workload of a single unit of workforce.

The recruitment pool contains d employees awaiting hire, covering all required skills, with the number of employees for each skill type exceeding the demand for that skill across tasks. According to written tests and interview results from recruitment, these employees differ in terms of monthly wage (k_d), service level (q_d), and digital technology acceptance (j_d).

To quantitatively assess workforce's service level (q_d) and digital technology acceptance (j_d), this study systematically organized the original written test and interview items used during recruitment and transformed them into two structured scales. Detailed questionnaires are provided in the Supplementary Materials. Both questionnaires have a maximum score of 100 points, and each item is measured using a 5-point Likert scale to ensure comparability and operational feasibility.

To verify the reliability and validity of the questionnaire, a small-sample pilot test was conducted in this study. The questionnaire was administered from 1 August 2025 to 14 September 2025. A total of 50 questionnaires were distributed, of which 41 valid responses were collected, yielding a response rate of 82%. The collected data were then imported into SPSS 26.0 for reliability and validity testing, and the results are as follows: Cronbach's α coefficients reached 0.73 (service level) and 0.76 (digital technology acceptance), meeting the acceptable threshold of 0.70 [45]. The KMO values based on principal component

analysis were 0.70 and 0.72, respectively, and Bartlett's test of sphericity was significant. These results confirm that the scales are suitable for quantifying workforce characteristics for subsequent optimization modeling.

This study aims to establish a multi-objective optimization model that balances three objectives to determine the optimal workforce allocation scheme: minimizing workforce wage costs, maximizing average workforce service levels, and maximizing average workforce digital technology acceptance. In the final allocation scheme, an employee d with skill t is assigned to an operational task l [16].

The additional assumptions are as follows:

- (1) Only the overall workforce demand during the operation stage is considered, without accounting for individual employee scheduling.
- (2) Each employee can be assigned to only one skill type for a single task, while a task may require employees with multiple skill types.
- (3) At least one employee must execute every skill a task requires. Depending on the task frequency defined in this study, each task may require multiple employees with the same skill to be completed.

3.2.2. Parameters and Variables

This subsection explains the notation used in the mathematical model.

- (1) Sets.
 D : employees; L : tasks; T : skill types.
- (2) Parameters.
 O_l : total workforce required for task l ;
 $N_{lt} \in \{0, 1\}$: whether task l requires skill t ;
 $M_{dt} \in \{0, 1\}$: whether employee d possesses skill t ;
 $W_{dl} \in \{0, 1\}$: whether employee d is available for task l ;
 $j_d \in [0, 100]$: digital technology acceptance score of employee d ;
 $q_d \in [0, 100]$: service level score of employee d ;
 $k_d \in [0, +\infty]$: monthly wage of employee d ;
 β : total budget for employee costs;
 γ_l : service level requirement of task l ;
 δ_l : digital technology acceptance requirement of task l ;
 U_{lt} : required number of type- t skilled employees with specific work experience for task l ;
 τ_d : number of workforce in the allocation scheme.
- (3) Decision Variable
 $u_{dlt} \in \{0, 1\}$: whether employee d with skill t is assigned to task l .

3.2.3. Mathematical Model

(1) Constraint Functions

The number of workforce assigned to each task must satisfy the demand (A1):

$$\sum_{d \in D} \sum_{t \in T} u_{dlt} \geq O_l, \forall l \in L \quad (6)$$

Assignment of non-required skills is not allowed (A2):

$$u_{dlt} \leq N_{lt} \forall d, l, t \quad (7)$$

A1 and A2 are sufficient to ensure that each task is matched with the required number of qualified personnel and that unnecessary skills are not assigned to tasks [16], thereby preventing infeasible solutions caused by understaffing or skill mismatches.

An employee is restricted to the execution of a single task (A3):

$$\sum_l u_{dlt} \leq W_{dl} \quad \forall d, l, t \quad (8)$$

Unlike the progress-driven tasks in the construction stage [23], workforce tasks in the operational stage are relatively fixed; for example, cleaning personnel perform fixed-area cleaning tasks daily. Therefore, this study introduces a task execution constraint for employees: if the value is 0, employee d is considered unavailable for task l and cannot be assigned.

Total budget constraint (A4):

$$\sum_{d,l,t} u_{dlt} k_d \leq \beta \quad (9)$$

Workforce compensation typically accounts for the majority of a building project's costs and is therefore a core indicator that managers must prioritize when developing workforce allocation strategies [19]. By introducing a budget constraint β , the solution process is restricted to searching within the budget-feasible solution space, ensuring that the final scheme is economically implementable [46].

Matching of skills and task demands (A5):

$$u_{dlt} \leq M_{dt} \text{ IF } N_{lt} = 1 \quad (10)$$

Service level constraint for individual tasks (A6):

$$u_{dlt} q_d \geq \gamma_l, \quad \forall l \quad (11)$$

Based on the minimum service requirements of operational tasks and the principle of workforce–task capability matching, this constraint is designed to ensure the executability of task assignments and the reliability of service quality [22]. By quantifying service requirements in the form of a “capability threshold,” the constraint restricts the solution space to only those feasible allocations that meet the minimum service standards [16].

Digital technology acceptance constraint for individual tasks (A7):

$$u_{dlt} j_d \geq \delta_l, \quad \forall l \quad (12)$$

Considering that different tasks require varying levels of digital technology acceptance [26]—for example, Customer service personnel must be proficient in using digital tools for collecting owner requests and coordinating workforce deployment, whereas Cleaning personnel only need to perform their work according to the information provided by digital technologies—this study introduces a threshold to constrain the digital technology acceptance capability of employees assigned to different tasks.

Qualification/experience constraint (A8):

$$\sum_{d \in \varepsilon_l} u_{dlt} \geq U_{lt}, \quad \forall l \quad (13)$$

Specifically, $\varepsilon_l = \{d | exp_d \geq \theta_{lt}\}$, safety-critical or quality-critical tasks (such as electrical maintenance) must be staffed with at least U_{lt} senior employee.

Service level consistency constraint (A9):

$$\max_{d:u_{dlt}=1} q_d - \min_{d:u_{dlt}=1} q_d \leq \Delta_l^{QD}, \forall l \quad (14)$$

For commercial buildings such as luxury hotels, where significant disparities in workforce service levels must be avoided [47], this study introduces a service level consistency constraint, allowing operators to set the constraint range according to actual needs.

(2) Objective Functions

Minimization of total workforce cost (B1):

$$\min(B1) = \sum_{d,l,t} u_{dlt} k_d \quad (15)$$

The control of workforce costs reflects the principle of economic efficiency in operational management [17,22]. Under the resource constraints defined in A4, further minimizing workforce costs enhances the economic sustainability of operations.

Maximization of workforce service level (B2):

$$\max(B2) = \frac{1}{\tau_d} \sum_{d,l,t} u_{dlt} q_d \quad (16)$$

Service Level reflects the service performance-oriented principle in operational management. In the O&M process of commercial buildings, the service capability of the workforce directly determines the quality and efficiency of task execution [4]. A higher level of service capability indicates that the workforce possesses stronger professional skills, adaptability, and service awareness, enabling them to perform specialized tasks efficiently [12], provide stable services to owners, and thereby enhance the overall reliability and responsiveness of operations.

Maximization of workforce digital technology acceptance (B3):

$$\max(B3) = \frac{1}{\tau_d} \sum_{d,l,t} u_{dlt} j_d \quad (17)$$

Objectives B1 and B2 constitute the core indicators for ensuring the stable execution of operational contract. Building upon this foundation, this study innovatively incorporates digital technology acceptance (B3) as the third optimization objective. As discussed in Section 2.2, the objective of digital technology acceptance responds to the digital development trend in building operations [13,28]. Enhancing the overall digital technology acceptance of the workforce can strengthen the organization's technological learning and innovation capabilities [16], thereby enabling digital technologies to function effectively throughout the operation process.

3.3. Solution Model Based on the NSGA-II

As a representative method of multi-objective optimization, the NSGA-II offers distinct advantages over commonly used mathematical programming approaches [8,48,49] and simulation methods [50–52]. Specifically, NSGA-II can effectively address the complex, multi-objective, and nonlinear optimization problems this research involves [53], while generating a well-distributed Pareto front in a single run, significantly reducing computational costs [1]. Moreover, compared with algorithms of the same type, such as NSGA-III, NSGA-II demonstrates superior performance in solving optimization problems with three or fewer objectives, which aligns with the problem characteristics of this study [53]. Due to these advantages, NSGA-II has been widely applied in solving multi-objective optimization

problems in commercial building operations, such as energy system configuration and cost control strategy design [1,53]. Based on its excellent theoretical foundation and practical effectiveness, this study employs NSGA-II to solve the mathematical model of workforce allocation strategies.

Design of the NSGA-II Algorithm

The design and computational steps of the NSGA-II algorithm are outlined below:

Step 1: Construction of the chromosome encoding scheme. In this study, the decision variables are represented using binary encoding, where the individual code of an employee is denoted as $D = [D_{11}, D_{12} \dots D_{1t}, D_{21} \dots D_{2t}, \dots D_{lt}]$. Here, D_{lt} indicates the assignment of an employee to task l with skill type t . For example, $D_{23} = 4$ means $u_{423} = 1$, denotes that employee 4 is assigned to task 2 with skill type 3 in the allocation scheme. This encoding method intuitively reflects workforce allocation's 0–1 assignment characteristics [16].

Step 2: Initialize the population and evaluate the fitness of individuals. Let the population size be N and the initial population be P . The initialization procedure is presented in Algorithm 1 (Table S2). The fitness function consists of three optimization objectives; hence, each individual has three fitness values: k_d , q_d , and j_d . During fitness evaluation, constraints are incorporated, and infeasible solutions are adjusted through a penalty function, as described in Algorithm 2 (Table S3).

Step 3: Apply fast non-dominated sorting to divide the population into different non-dominated fronts, and adopt an elitist preservation strategy by combining crowding distance, thereby maintaining the diversity and distribution of the solution set during the evolutionary process [50].

Step 4: In the evolutionary process of the population, selection, crossover, and mutation operations are performed sequentially. The selection operation adopts tournament selection based on non-dominated rank and crowding distance to ensure the inheritance of high-quality individuals. The crossover operation employs single-point or multi-point crossover to generate new solution combinations. The mutation operation randomly flips individuals' gene positions to enhance the population's exploratory capability [53].

Step 5: The iterative process terminates when the predefined convergence criterion is met, and the algorithm outputs a set of approximate Pareto-optimal solutions.

3.4. Scheme Evaluation Based on CRITIC and VIKOR

After solving the mathematical model with the NSGA-II algorithm in Section 3.3, a set of Pareto solutions was obtained, each corresponding to a workforce allocation scheme. However, according to existing research, under multi-objective optimization scenarios, the solutions within the Pareto set often exhibit varying degrees of objective conflict [54–56], necessitating further objective evaluation and the selection of a compromise solution.

Among existing evaluation methods, AHP relies heavily on expert judgment for weighting [55], making it highly subjective and unsuitable for the semi-automated decision-making process developed in this study. TOPSIS is sensitive to the normalization method and tends to favor solutions closest to the ideal point [56], making it difficult to reflect trade-offs between conflicting objectives. In view of this, the CRITIC–VIKOR method is adopted in this study: CRITIC generates objective weights based on the contrast intensity and degree of conflict among indicators [37], thereby avoiding human intervention; VIKOR, following the principle of minimizing overall regret [57], can identify solutions with compromise advantages from the Pareto set [46]. Therefore, the CRITIC–VIKOR method aligns well with the non-dominated solution set produced by NSGA-II and can objectively determine the

optimal decision scheme along the Pareto frontier. The entire CRITIC–VIKOR procedure was implemented in MATLAB R2020b.

3.4.1. CRITIC

The CRITIC method, derived as an improvement of the Entropy method, employs the standard deviation to measure the degree of variation within an objective, while simultaneously using correlation coefficients to capture the interrelationships among objectives [37]. The specific steps are as follows:

- (1) Calculate the standard deviation of each objective based on the objective data from the Pareto solution set obtained by the NSGA-II algorithm;
- (2) Calculate the correlation coefficients among the objectives;
- (3) Calculate the objective weights w_i of each objective.

3.4.2. VIKOR

The VIKOR method is a multi-criteria decision-making approach that can select the optimal compromise solution from the Pareto front obtained by the NSGA-II algorithm [57]. The specific steps are as follows:

- (1) Normalize the data of the three objectives obtained from the Pareto front generated by the NSGA-II algorithm.
- (2) Calculate the ideal and negative-ideal solutions.

For ideal objectives (B2, B3):

$$f_j^* = \max_i z_{ij}, f_j^- = \min_i z_{ij} \quad (18)$$

For negative-ideal objective (B1):

$$f_j^* = \min_i z_{ij}, f_j^- = \max_i z_{ij} \quad (19)$$

- (3) Compute the distances from the ideal solution.

$$S_i = \sum_j w_j \frac{f_j^* - z_{ij}}{f_j^* - f_j^-} \quad (20)$$

$$R_i = \max_j \left(w_j \frac{f_j^* - z_{ij}}{f_j^* - f_j^-} \right) \quad (21)$$

Here, S_i denotes the overall gap, reflecting the weighted average deviation from the ideal solution. R_i denotes the the maximum gap, reflecting the disadvantage of the worst-performing objective.

- (4) Calculate the compromise index Q .

$$Q_i = v * \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \quad (22)$$

Here, S^* denotes the minimum value of S_i , and S^- denotes its maximum value; the same applies to R^* and R^- . v is the compromise parameter, which, following empirical values from existing studies, is set to 0.5 in this study [57].

- (5) Rank alternatives and identify the best solution.

Rank the solutions in ascending order of Q values to determine the priority of compromise solutions. Next, if the best solution satisfies the following two conditions, it is considered the unique compromise solution. Acceptable advantage condition:

$$Q(Z(2)) - Q(Z(1)) \geq \frac{1}{m-1} \quad (23)$$

where m is the number of alternatives, and $Z(2)$ denotes the second-best solution.

Acceptable Stability Condition: The best-ranked solution $Z(1)$ must also rank first in either S or R .

4. Case Study

To validate the model and algorithm proposed in this study, a case study was conducted on the new campus of a university in Shandong Province, China [37]. As a representative type of commercial building [32], university campuses exhibit a high degree of complexity and diversity in both functional composition and spatial form [58]. Their O&M activities are characterized by considerable diversity and specialization, and are typically outsourced by the owner (the university) to professional property management companies [37]. These features provide an ideal application scenario for validating the proposed workforce allocation model. Accordingly, the study takes the workforce allocation scheme of the property operation team in the new campus as an example to demonstrate the application process of the proposed model and algorithm.

4.1. Case Information

The new campus entered the operational stage in September 2023. An operation contract was signed between the university and the property management operator, delegating on-campus property services and maintenance tasks to the operator. These tasks span eight categories of facilities—including classrooms, gymnasiums, and student residences—as well as campus-wide services such as landscaping and security. In accordance with contractual requirements, the operator independently organizes and deploys its workforce to carry out the necessary operational activities.

Between September 2023 and September 2024, the student population on campus reached less than one quarter of the expected maximum, and therefore, workforce allocation only partially met the contract requirements. With the progress of the enrollment plan, the campus gradually moved toward full capacity, necessitating comprehensive adjustments and improvements to the workforce allocation strategy.

4.2. Workforce Demand Identification

First, the constructed NLP model was first applied to process the operation contract, automatically identifying operational tasks and matching workforce types, with minor corrections made to mismatches in the results. The final results, as shown in Table 3, identified 14 operational tasks involving 13 categories of workforce types. Next, the required workforce quantities for each type of task are calculated according to Equations (1)–(5). The detailed parameters of the case are provided in the Supplementary Materials as Table S4.

Table 3. NLP-identified tasks and matched workforce types.

Code	Task	Task Frequency	Workforce Types	Workforce Demand
cp	custodial services for interior and exterior spaces sweeping dusting and mopping occupant support services meaning arranging for seating	Daily tasks	Cleaning personnel	16
la	exterior movable furniture and supplying teaching aids and equipment	Daily tasks	Laborer	4
sp	security services daily operation of interior and exterior security systems	24 h tasks	Security personnel	14
cs	provide a single customer services center for the existing campus and the facilities	24 h tasks	Customer service personnel	5
el	maintain and renew electrical infrastructure equipment	Periodic tasks	Electrician	6
es	maintain and renew all elevator and vertical transportation systems	Periodic tasks	Elevator service specialist	4
fm	inspect test maintain and renew fire protection and life safety systems	Periodic tasks	Fire management personnel	4
ga	operation of the irrigation system weeding mowing and grass cutting	Periodic tasks	Gardeners	5
hv	operate maintain and renew HVAC equipment and systems	Periodic tasks	HVAC system technician	4
in	provide maintain and upgrade it infrastructure are necessary	Periodic tasks	Information systems administrator	4
fa	maintain and renew all the facility envelopes structures	Periodic tasks	Mason	3
ar	maintain and renew all architectural finishes	Periodic tasks	Mason	4
pa	furnish all supervision labor materials and equipment necessary to remediate occurrences of vandalism or graffiti	Periodic tasks	Painter	2
pl	operate maintain and renew the plumbing system and equipment	Periodic tasks	Plumber	4

4.3. Algorithm Implementation

Based on the NLP recognition results and the operator's actual requirements, the parameters of the mathematical model constructed in Section 3.2.3 were specified. Subsequently, the parameters of the NSGA-II algorithm were adjusted in MATLAB R2020b according to the mathematical model. Finally, the NSGA-II algorithm was executed on a PC with a 2.40 GHz Intel (R) Core (TM) i5-3600H CPU. After multiple test runs, the final parameter settings of the algorithm are presented in Table 4. Based on the operator's actual

budget and the operator's additional requirements for each task, the parameter settings of the constraints in the optimization process were determined, as shown in Table 5.

Table 4. Parameters of the NSGA-II Algorithm.

Objectives	Crossover Ratio	Mutation Ratio	MaxIt
3	0.7	0.4	400

Table 5. Parameters of the constraint conditions.

Constraint Code	Constraint Parameter
A1	$O_{cp} = 16 \ O_{cs} = 5 \dots\dots O_{pl} = 4$
A4	$\beta = 460000$
A6	$\gamma_{cs} = 60 \ \gamma_{fm} = 60 \ \gamma_{es} = 50$
A7	$\delta_{cs} = 60 \ \delta_{in} = 60$
A8	$U_{in} = 2 \ U_{fm} = 1 \ U_{el} = 2 \ U_{es} = 1$

The iterative curves of each objective during the algorithm's iterations are shown in Figure 2. When the algorithm terminates upon reaching the maximum number of iterations, a series of Pareto-optimal solutions satisfying the constraints is generated. As illustrated in Figure 3, each solution in the solution set corresponds to a workforce allocation scheme, with the detailed information of the solution set presented in Table 6.

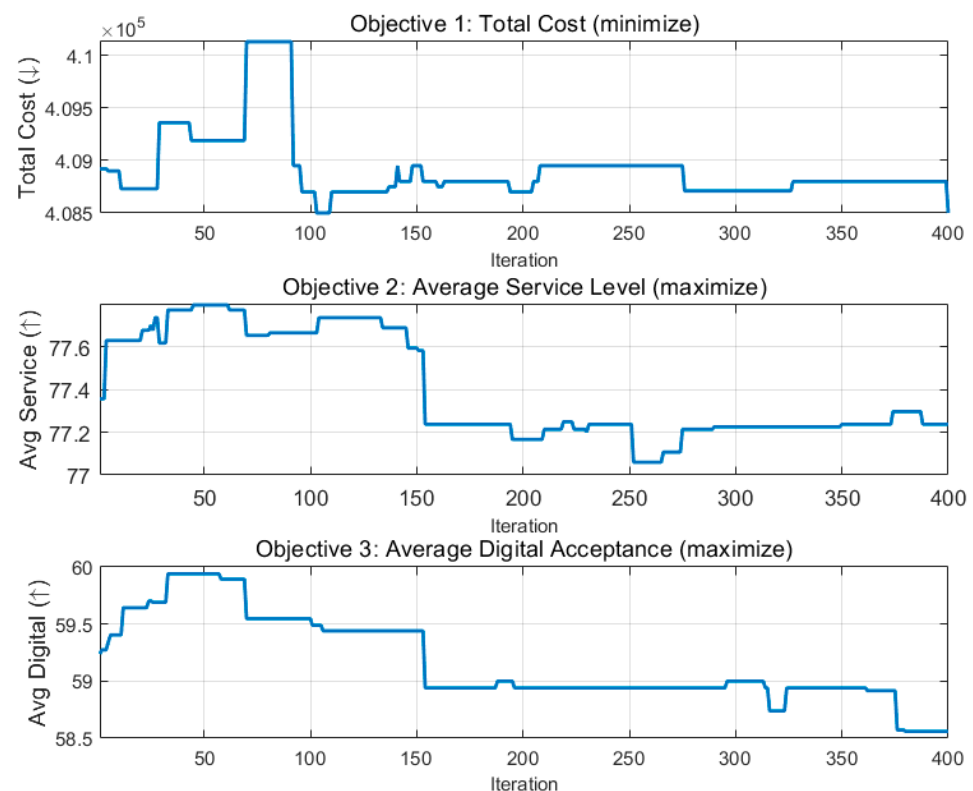


Figure 2. Iterative process of the algorithm.

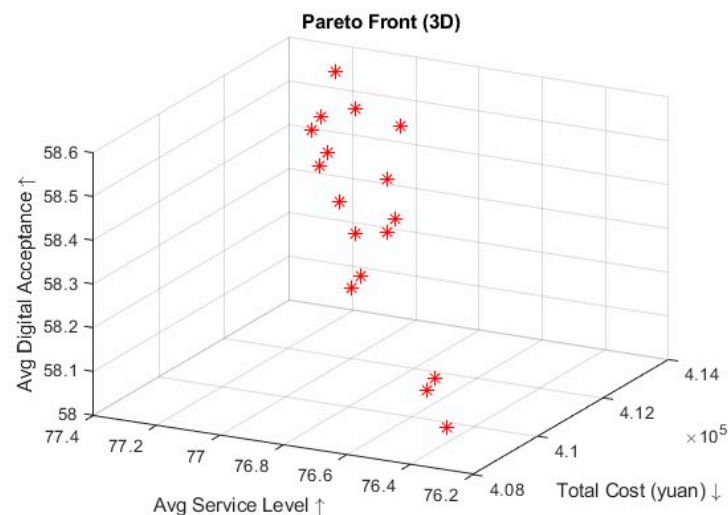


Figure 3. Results of the algorithm.

Table 6. Pareto solution set.

Code	Total Workforce Cost/CNY	Workforce Service Level	Workforce Digital Technology Acceptance
1	413,830	77.23809524	58.54761905
2	411,050	76.78571429	58.47619048
3	412,810	77.1547619	58.41666667
4	411,610	76.92857143	58.21428571
5	412,660	77.16666667	58.39285714
6	408,800	76.42857143	58.13095238
7	411,800	76.82142857	58.55952381
8	410,350	76.71428571	58.39285714
9	410,500	76.70238095	58.41666667
10	412,360	77.07142857	58.33333333
11	413,160	77.21428571	58.47619048
12	412,260	77.01190476	58.27380952
13	408,950	76.41666667	58.15476190
14	408,500	76.33333333	58.07142857
15	411,460	76.94047619	58.19047619
16	413,530	77.14285714	58.48809523
17	413,030	77.22619047	58.45238095

To verify the superiority of the NSGA-II algorithm in solving the optimization problem of this study, the mathematical model was also solved using the NSGA-III algorithm, and the average values of each objective in the Pareto solution set were calculated. These averages were then compared with those of NSGA-II and the operator's expected values. The results are presented in Table 7.

Table 7. Algorithm Comparison.

Code	Total Workforce Cost/CNY	Workforce Service Level	Workforce Digital Technology Acceptance
NSGA-II	411,568	76.89985994	58.3522409
NSGA-III	413,554	75.26428571	57.1678571
Expected Value	46,0000	65	50

It can be observed that, compared with the operator's expected values, both algorithms achieved optimization. However, in the context of the three-objective optimization

problem, although NSGA-III can guide the search through reference points and forcibly push solutions toward different reference directions to obtain a broader Pareto front [59], the results for all three objectives were inferior to those obtained by NSGA-II. Therefore, this study continues to adopt the Pareto solution set generated by NSGA-II as the basis for subsequent decision-making, from which the optimal scheme is selected.

4.4. Scheme Evaluation

Following the methodology, the CRITIC method was first applied to the 17 Pareto solutions to compute the objective weights w_i of the three optimization objectives. The results are presented in Table 8.

Table 8. Objective weights of the objectives.

	Total Workforce Cost	Workforce Service Level	Workforce Digital Technology Acceptance
w_i	0.4514966	0.29766368	0.25083972

Subsequently, the VIKOR method was applied using Equations (18)–(23) to evaluate and rank the schemes, from which the optimal scheme was selected. The results are presented in Table 9. It can be seen that Scheme 8 achieved the highest ranking and satisfied both the acceptable advantage and acceptable stability conditions of the VIKOR method, thereby being identified as the optimal allocation scheme.

Table 9. Evaluation results of the VIKOR method.

Scheme	S	R	Q	Rank
1	0.4576	0.4515	0.6773	14
2	0.4077	0.2160	0.0782	3
3	0.4659	0.3651	0.5521	9
4	0.5427	0.2634	0.6426	13
5	0.4615	0.3524	0.5138	6
6	0.5120	0.2663	0.5387	8
7	0.4166	0.2795	0.2238	4
8	0.4147	0.1723	0.0250	1
9	0.4191	0.1762	0.0475	2
10	0.4981	0.3270	0.5979	11
11	0.4454	0.3947	0.5323	7
12	0.5398	0.3185	0.7307	16
13	0.5164	0.2702	0.5613	10
14	0.5485	0.2977	0.7245	15
15	0.5383	0.2507	0.6042	12
16	0.4941	0.4261	0.7614	17
17	0.4427	0.3837	0.5030	5

Compared with the operator's expectations, Scheme 8, while satisfying all task constraints, reduced total workforce costs by 10.79%, increased average service level by 18.02%, and improved average digital technology acceptance by 16.79%, thereby achieving the optimization objectives. From the vertical comparison in Table 6, Scheme 8 shows only about a one-point decrease in average service level compared with Scheme 1, which has the highest service level, yet it saves 3480 CNY in labor costs—an amount equivalent to a cleaner's monthly salary. Moreover, although the high-service scheme requires a substantial increase in labor cost, its digital technology acceptance does not improve to a comparable extent, indicating low marginal input–output efficiency. Based on the trade-offs among these three objectives, the compromise Scheme 8 identified by the CRITIC–VIKOR method maintains a

relatively high service level while achieving more reasonable cost control, providing a more feasible, stable, and economically sound allocation pathway for operational management. This result assists the campus operator in comprehensively planning the current workforce allocation strategy and selecting employees from the recruitment pool who are better suited to operational needs.

5. Discussion

5.1. Impact of Location Conditions on Workforce Allocation

The optimization results of the case study indicate that although the optimal allocation scheme improved the digital technology acceptance of the operation team, the average value of this objective within the Pareto front remained relatively low, as shown in Table 6. This phenomenon is closely related to the characteristics of the original dataset used in the study [37]. The dataset was derived from written tests and interviews conducted during the operator's early recruitment process, in which the case's location conditions significantly impacted the workforce resource. The campus is located in a remote township far from the urban area, and to control operational costs, the operator primarily recruited workforce from surrounding villages. Due to the short commuting distance, the operator was not required to provide additional housing, further reducing workforce costs.

However, location conditions also impose significant constraints on workforce acquisition and allocation. Workforce from rural areas often possess practical experience in traditional positions such as cleaning and security, enabling them to maintain a basic service level. But their overall acceptance of digital technologies remains low, making it difficult to meet the growing demand for digitalization and intelligent building operations. On the other hand, since the case campus is more than 50 km from the nearest urban area, attracting external workforce with higher levels of digital literacy remains difficult, even if the operator increases wages or provides housing. This practical constraint results in allocation schemes generated by the optimization model that are relatively reasonable in cost control and service level, but difficult to improve in digital technology acceptance further. Notably, such workforce allocation issues arising from location constraints are not unique to China [42,60]; similar findings have been reported in studies from countries and regions such as Australia [61] and the United States [62], suggesting that this is a widespread challenge.

In summary, this study recommends that operators incorporate workforce digital technology acceptance differences into the cost assessment framework to address the constraints imposed by location conditions on workforce allocation in commercial building operations. Specifically, retraining costs can be converted into wage costs, so that subsequent digital technology retraining plans during operation are already considered when applying the proposed optimization model. Under this scheme, operators may gradually mitigate capability gaps caused by location disadvantages through multi-level training mechanisms [47,63], such as periodic training, pre-employment digital courses, and scenario-based practical exercises. This recommendation can also be applied to address other skill gaps in the workforce [64], not only facilitating optimal allocation under existing conditions but also enhancing the workforce's overall quality and adaptability to new technologies through long-term workforce capital investment, thereby strengthening the sustainability of commercial building operation management.

5.2. The Innovation of Integrating BERT and NSGA-II

This study proposes an integrated BERT-NSGA-II workforce resource allocation optimization model, which not only addresses the research gap in workforce allocation during the operational stage of commercial buildings but also demonstrates significant

methodological innovations. In the field of engineering management, existing optimization research often focuses on improving algorithmic performance [31,54], while paying insufficient attention to whether the input parameters of the optimization model accurately capture project-specific requirements. As a result, optimization outcomes may be misaligned with practical project demands. In contrast, this study introduces a BERT-based NLP model to automatically identify and classify operational tasks and workforce categories from contract texts, transforming unstructured provisions into structured inputs for optimization. This automated demand recognition mechanism strengthens the correspondence between optimization models and project requirements. Building upon this foundation, the NSGA-II algorithm is employed to solve the multi-objective optimization problem, simultaneously balancing workforce costs, service levels, and digital technology acceptance, while ensuring that the resulting allocation schemes can be effectively implemented in operation management. More importantly, the proposed BERT-NSGA-II integrated framework provides a replicable methodological paradigm for workforce allocation, which can be extended to other types of infrastructure and building operation scenarios, thus broadening the application boundaries of Genetic Algorithm and NLP techniques in engineering management.

5.3. Practical Prerequisites for Implementing the Decision Support Tool

Although the NLP, NSGA, and VIKOR modules within the integrated model already enable automated processing, several implementation prerequisites must still be considered when applying the proposed model in practice. First, a structured data collection mechanism is required to ensure the availability of intact contracts, workforce skill profiles, salary information, and digital competency assessment data. Second, the operating organization needs to possess at least a basic level of programming capability, which involves feeding raw data into the model and transferring data across different software tools. Finally, successful implementation depends on institutional readiness, including managerial understanding of the model's assumptions, acceptance of data-driven decision-making, and alignment with existing human resource and budgeting policies. Only by meeting these prerequisites can the proposed framework be effectively deployed in real-world facility management settings.

5.4. Limitations and Future Directions

The model framework developed in this study is primarily applicable to commercial buildings that adopt an outsourced operation model [9]. However, for building projects where owners organize and manage operational activities by themselves, the NLP module is not applicable due to the absence of formal operation contracts. Nevertheless, owners can still utilize the NSGA-II optimization component to perform multi-objective optimization of workforce allocation strategies.

In addition, this study still has some main limitations. First, to account for differences in commercial building type, floor area, and other parameters, workforce numbers were calculated using traditional formulas, which can be time-consuming when estimating workforce demand for large-scale commercial buildings. Second, although the optimization model considers service level and digital technology acceptance, key parameters and thresholds were determined based on case-specific assessments and managerial rules. This limits transparency and generalizability. Standardized data collection protocols or multi-case studies could address this issue in future work.

Third, the optimization model did not incorporate detailed workforce scheduling. Therefore, future research should focus on collecting extensive operational data and applying predictive techniques such as neural networks to forecast workforce numbers demand

based on the specific operational characteristics of commercial buildings. On this basis, workforce scheduling can be integrated into the proposed model to achieve more fine-grained optimization.

6. Conclusions

This study developed a workforce allocation optimization model for the operational stage of commercial buildings based on BERT and NSGA-II. The model provides operators with a practical decision-support tool for workforce allocation and helps overcome the misaligned strategies that often result from reliance on empirical methods. The main findings are as follows:

- (1) The workforce type identification and classification model developed based on BERT achieved performance metrics of Accuracy = 0.79, Precision = 0.79, Recall = 0.80, and F1 = 0.78, consistent with the average level of existing multi-label classification models. The model's output provides a fundamental framework for allocation optimization, effectively enhancing the alignment of optimization results with the actual operational demand of commercial buildings.
- (2) Using the workforce allocation of a university campus property management team in China as a case study, the NLP model identified 14 operational tasks involving 13 workforce categories based on the operation contract. The NSGA-II model achieved multi-objective optimization under workforce allocation constraints, while the CRITIC–VIKOR method objectively selected the optimal scheme from the Pareto solution set. The results show that, compared with the operator's expectations, the optimal scheme reduced workforce wage costs by 10.79%, increased average service levels by 18.02%, and improved average digital technology acceptance by 16.79%. The above results validate the effectiveness of the proposed model in this study.
- (3) Discussion of the optimization results highlights the constraints of location conditions on commercial building workforce allocation. To address this issue, the study proposes converting employee retraining costs into wage costs, thereby incorporating workforce retraining into the optimization process. Retraining during operation can help compensate for the workforce capability disadvantages caused by unfavorable location conditions.

The main contributions of this study are as follows. Theoretically, it proposes a mathematical optimization model for workforce allocation strategies, with wage cost, service level, and digital technology acceptance as optimization objectives. This research fills a gap in workforce allocation studies during the operational stage of commercial buildings and, for the first time, introduces workforce digital technology acceptance into the workforce allocation problem in the construction domain.

At the practical level, the optimization model integrating BERT, NSGA-II, and the CRITIC–VIKOR method realizes a semi-automated decision process of “demand identification-allocation optimization-optimal scheme selection.” It provides a practical decision support tool for commercial building operators to improve workforce management, thereby promoting the sustainable operation of commercial buildings.

Future research should incorporate predictive algorithms to effectively calculate the quantity of workforce required and take employees' specific scheduling into account, enabling more detailed and refined workforce allocation optimization.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/buildings16020289/s1>, Table S1: Hyperparameter tuning of the baseline models; Table S2: Pseudocode of algorithm 1; Table S3: Pseudocode of algorithm 2; Table S4: Workforce demand parameters for the case study.

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Abbreviations

The following abbreviations are used in this manuscript:

NLP	Natural Language Processing
NSGA-II	Non-dominated Sorting Genetic Algorithm II
BERT	Bidirectional Encoder Representations from Transformers
TF-IDF	Term Frequency–Inverse Document Frequency
LR	Logistic Regression
SVM	Support Vector Machine
RF	Random Forest

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