INTEGRATED MANY-OBJECTIVE OPTIMIZATION FOR DECISION-MAKING AND DYNAMIC PROJECT CONTROL

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Abstract

Construction projects involve conflicting objectives beyond time and cost, including quality, safety risk, resource stability, and environmental impact. Many-objective optimization (MaOO) helps address this complexity in planning, but it provides limited support for decision-making during execution, and selecting one solution from Pareto-sets often depends on human judgment. To overcome these gaps, this paper proposes an integrated planning and control framework combining Opposition-Based NSGA-III (OBNSGA-III) for six-objective optimization, an Entropy-based-VIKOR model for compromise solution selection, and a Dynamic-MaOO re-optimization mechanism for execution control. A case study based on 25-activities is used to demonstrate effective decision support from planning to execution.

Introduction

Construction projects operate as short-term complex production systems that involve multiple stakeholders with different and competing objectives (Ward et al. 1991). Construction industry is one of the rapidly growing industries in developing nations that supports socio-economic development by contributing infrastructure growth and employment generation. (Fu & Zhang, 2016). Construction projects involve large number of individual but interlinked activities. (Singh and Ernst, 2011). Traditional construction projects focus only on optimization of Time and cost. But Construction projects involve large number of objectives such as Quality, safety risk, resource moment, and environmental impact due to construction. These are important objectives for stakeholders and have direct impact on the project.

Traditional multi-objective algorithms struggle to maintain solution diversity and convergence to optimize more than three objectives. Thus, simultaneously optimization of these objectives requires many objective optimizations model (MaOO). NSGA-III and its variants address this issue through reference-point-based selection mechanisms, enabling efficient search in high-dimensional objective spaces.

MaOO model gives pareto optimal solution sets. Decision makers often use subjective weighted-sum methods to select one solution from the Pareto solution sets for the project. This includes human factor and limiting reproducibility. Current construction MaOO research, optimize the project objectives during planning phase assuming that selected solution will remain valid during execution phase.

The proposed framework integrates Opposition-Based NSGA-III (OBNSGA-III) model, an Entropy-based-VIKOR model, and Dynamic-MaOO re-optimization mechanism. This integrated framework contributes as a new methodology in selection of single solution set from sets pareto-optimal solution and plays a key role in project control during execution phase as it moves beyond one-time optimization and supports planning as a continuous process and enables both initial decision-making and execution-stage adaptation.

Literature Review

Early research in construction projects optimization was largely focused on the optimization of time–cost and finding the relationship between project duration and direct cost. Abbasnia et al. (2008) applied fuzzy logic model to find uncertainty in time–cost relationships, while Zareei and Hassan-Pour (2015) introduced a resource-constrained formulation to improve the schedule feasibility. These studies showed that deterministic planning approaches are insufficient for realistic construction decision making. As research progressed, it is found that considering only two objectives are not sufficient, particularly in projects where schedule acceleration adversely affected other performance dimensions.

To address this, quality was introduced as a third optimization objective. El-Rayes and Kandil (2005) demonstrated that minimization of time and cost alone can significantly degrade the construction quality and used an integrated time–cost–quality optimization model. The emergence of evolutionary algorithms further enabled the treatment of such multi-objective problems. Deb et al. (2002) proposed a NSGA-II algorithm. This model was widely adopted in construction scheduling as it provides elitist selection, and it has ability to generate diverse Pareto-optimal solutions. Subsequent studies applied genetic algorithms and particle swarm optimization to incorporate additional constraints and objectives, including safety risk and resource utilization (Afshar, A., and Dolabi, 2014; Elbeltagi, E., 2016).

As construction performance evaluation expanded, researchers have studied the effects of optimization of safety and environmental impact with time and cost. Afshar, A., and Dolabi (2014) showed that time–cost-optimized schedules often lead to higher safety risks and came with a time-cost-safety risk optimization model, while Ozcan-Deniz et al. (2012) demonstrated a significant trade-off between productivity and environmental impact. Further, multi-mode, resource-constrained formulations highlighted the conflict between stability of execution and traditional performance measures of project (Ghoddousi, P., et al., 2013; Kim, K., et al., 2015). At this stage, most models address three objectives, typically combining time, cost and either safety or environmental criteria.

However, as the number of objectives increased beyond three, the conventional dominance-based algorithms such as NSGA-II, the effectiveness and diversity of selected solutions decreased. To overcome this, Deb and Jain (2014) proposed a reference-based NSGA-III algorithm. This algorithm uses a reference-point-based non-dominated sorting to maintain diversity in high-dimensional objective spaces. Development of this method marked a transition from multi-objective optimization to many-objective optimization in construction research. Arya et al. (2024) and Behera et al. (2025) applied NSGA-III to balance time, cost, quality, and sustainability-related objectives, while Zhan et al. (2024) demonstrated its effectiveness in generating well-distributed Pareto fronts for construction project management problems.

Recent studies have explicitly acknowledged the need for five-objective optimization frameworks. Panwar and Jha (2019) formulated a many-objective construction scheduling model integrating time, cost, resources and environment impact and Sharma and Trivedi (2022) integrated time, cost, quality, safety, and resource constraints using NSGA-III-based approaches. Panthi and Hussain (2025) further extended this line of research by proposing an OBNSGA-III framework incorporating time, cost, quality, safety, and environmental sustainability. Similarly, Sharma and Trivedi (2023) modelled trade-offs among time, cost, quality, safety risk, and environmental impact using opposition-based NSGA-III. These studies collectively demonstrate that most existing construction MaOO models converge at five objectives, reflecting both computational complexity and modelling challenges.

Despite of these advances, construction research optimization models are rarely used to optimize six-objectives simultaneously. In particular, the simultaneous integration of time, cost, quality, safety risk, environmental impact, and resource moment within a single optimization framework has received limited attention. Resource moment objectives are often treated separately from safety or environmental criteria, even though all three directly influence production stability and execution reliability. The absence of six-objective formulations restricts the ability of planners to evaluate comprehensive trade-offs inherent in complex construction systems.

Another limitation in literature is the decision-making to select one solution from Pareto-optimal sets. Although NSGA-III-based models generate diverse solution fronts, most studies rely on subjective weighting or visual inspection to select final execution plans. Zhan et al. (2024) explicitly noted that post-optimization decision selection remains weak in construction optimization research. While entropy-based weighting and compromise ranking methods such as VIKOR have been suggested to reduce subjectivity, their systematic integration with many-objective optimization models is still limited.

The majority of existing many-objective construction optimization studies are static and focusing exclusively on the planning stage only. Once project execution starts, the deviations in objective values are typically managed through heuristic rescheduling not from the original optimization logic.

In summary, the literature reveals three interrelated gaps: (1) most construction optimization studies are limited to five objectives, (2) decision-making from many-objective Pareto fronts remains weak and often subjective, and (3) optimization frameworks rarely extend into execution-stage control. The present research addresses these gaps by formulating a six-objective many-objective optimization model, integrating objective decision selection using Entropy–VIKOR, and embedding the model within a dynamic planning-and-control framework suitable for construction production systems. re-optimization.

From a lean construction point of view, construction projects are similar to production systems where planning and control must be continuously aligned to manage variability and improve the workflow reliability. Foundational lean construction studies emphasize the importance of reduction of uncertainty from the production and adapting plans that are based on execution feedback rather than relying on static schedules (Koskela, 1992; Ballard and Howell, 1998). The existing optimization literature remains focused only on planning-stage solutions. The proposed framework responds to this gap by supporting adaptive decision-making during execution phase of project.

Methodology

This research adopts a planning–control perspective to address construction projects as dynamic production systems rather than static optimization problems. The proposed methodology integrates three complementary components:

1. Many objective planning by using OBNSGA-III
2. Objective compromise decision selection using Entropy–VIKOR
3. Dynamic re-optimization during execution.

The proposed framework integrates optimization, decision selection, and re-optimization into a single workflow. The study shows how these can be used together to support planning and control decisions in multimode construction projects.

This model integrates structure existing optimization and decision-making tools into a coherent framework that supports both planning and execution-stage control. This approach aligns with lean construction principles, where plans are continuously optimized and adjusted based on execution feedback instead of being fixed at the outset. This structure explicitly links planning and control, addressing a major limitation of static construction optimization models.

In this study, the VIKOR method is employed to support compromise decision-making under conflicting criteria. The method determines a compromise solution by maximizing group utility and minimizing individual regret, thereby balancing both overall performance and the worst-case criterion. Other techniques, such as TOPSIS, rely on distances to ideal and negative-ideal solutions without considering their relative importance, which may affect the ranking results in certain decision situations (Opricovic, S., and Tzeng, G. H., 2004). As a result, VIKOR provides a more reliable and decision-relevant solution, particularly in situations where poor performance in a critical criterion cannot be ignored.

Many-Objective Optimization Model

Decision Variables and Project Representation

The construction project is modelled as a **precedence-constrained activity network** consisting of n activities. Each activity A has multiple execution modes m, where each mode represents a distinct combination of:

- Activity completion time (ACT_A)
- Activity completion cost (labour, material, equipment) (ACC_A)
- Activity Quality index (AQI_A)
- Activity Safety risk (ASR_A)
- Activity Environmental impact (AEI_A)
- Activity Resource moment (R_t^k)
- A candidate solution is defined as a vector of execution modes, one for each activity.

Objective Function Formulation

The model simultaneously optimizes six project-level objectives, the formulation of objectives are as below:

Objective 1: Minimize Project Completion Time (PCT)

$$PCT = \sum_{A \in CP} A\,CT_A \tag{1}$$

Where, CP denotes the set of activities on the critical path.

Objective 2: Minimize Project Completion Cost (PCC)

$$PCC = \sum_{A=1}^{n} D\,C_A + (IDC \times PCT) \tag{2}$$

Where, DC_A is the direct cost of activity A and IDC is the indirect cost per day.

Objective 3: Maximize Project Quality Index (PQI)

$$PQI = \frac{1}{n}\sum_{A=1}^{n} A\,QI_A \tag{3}$$

Where, AQI_A represents the quality achieved during first-time execution of activity A.

Objective 4: Minimize Project Safety Risk (PSR)

$$PSR = \sum_{A=1}^{n} A\,SR_A \tag{4}$$

Where, ASR_A aggregates safety risks related to labor injury, material wastage, and equipment failure for activity A.

Objective 5: Minimize Project Environmental Impact (PEI)

$$PEI = \sum_{A=1}^{n} A\,EI_A \tag{5}$$

Where, AEI_A is the CO_2-equivalent emission associated with activity A.

Objective 6: Minimize Project Resource Moment (PRM)

$$PRM = \sum_{A=1}^{n} A\,RM_A \tag{6}$$

here, $ARM_A = M_x + M_y$ $M_x = \sum (R_t^k)^2$, $M_y = \sum (R_t^k \cdot t)$

This formulation penalizes resource fluctuation and uneven resource distribution over time.

OBNSGA-III Optimization Procedure

The many-objective optimization problem is solved using Opposition-Based NSGA-III (OBNSGA-III).

The algorithm proceeds as follows:

1. Generate an initial random population of size N based on execution modes.
2. Generate an opposition-based population by computing opposite solutions and selecting the fittest N individuals.
3. Generate structured reference points using: $H = \binom{N+p-1}{p}$; where $N = 6$ objectives and $p = 6$ divisions per objective.
4. Apply simulated binary crossover (SBX) and polynomial mutation to generate offspring. And combine parent and offspring populations and perform non-dominated sorting.
5. Normalize objective values and associate solutions with reference directions.
6. Apply niche-count-based selection using perpendicular distance to reference points.
7. Perform opposition-based generation jumping.
8. Repeat until convergence criteria are met.

This process yields a diverse Pareto-optimal solution set without requiring subjective preferences during optimization.

Entropy–VIKOR Decision-Making Model

To identify a single actionable solution from the Pareto sets, an **Entropy-based VIKOR** model is employed.

Formulation of Entropy–VIKOR Decision-Making Model

Let the Pareto-optimal solution set obtained from OBNSGA-III be denoted as:

$$\mathcal{P} = \{P_1, P_2, \dots, P_m\}$$

Each solution P_i is evaluated against M objectives, forming a decision matrix F:

$$\mathrm{F} = [f_{ij}], \quad i = 1,2,\dots,m; \ j = 1,2,\dots,M$$

where f_{ij} represents the value of the j^{th} objective for the i^{th} Pareto solution.

Entropy-Based Objective Weighting

To eliminate subjective bias in assigning objective importance, entropy theory is applied.

Step 1: Normalization of Decision Matrix

Since the objectives are measured in different units and possess different optimization directions, the decision matrix must be normalized.

For each objective j, the normalized performance value p_{ij} is computed as:

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^{m} f_{ij}} \tag{7}$$

Step 2: Entropy Calculation

The entropy value E_j of the j^{th} objective is calculated as:

$$E_j = -\frac{1}{ln(m)} \sum_{i=1}^{m} p_{ij}\, ln(p_{ij}) \tag{8}$$

The entropy value reflects the degree of dispersion of information associated with an objective across Pareto solutions.

Step 3: Objective Weights

The entropy-based weight w_j of the j^{th} objective is then obtained as:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{M} 1 - E_j} \tag{9}$$

Objectives exhibiting greater variability across Pareto solutions are thus assigned to higher importance.

VIKOR Compromise Ranking

The VIKOR method is employed to rank Pareto-optimal solutions and identify a compromise solution.

Step *1*: Determination of Best and Worst Values

For each objective j, the best and worst values are defined as:

$$f_j^* = \begin{cases} \underset{i}{min} f_{ij}, & \text{for cost-type objectives} \\ \underset{i}{max} f_{ij}, & \text{for benefit-type objectives} \end{cases}$$

$$f_j^- = \begin{cases} \underset{i}{max} f_{ij}, & \text{for cost-type objectives} \\ \underset{i}{\min} f_{ij}, & \text{for benefit-type objectives} \end{cases}$$

Step 1: Group Utility and Individual Regret Measures

The **group utility measure** for solution i is computed as:

$$S_i = \sum_{j=1}^{M} w_j \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \tag{10}$$

The **individual regret measure** is defined as:

$$R_i = \underset{j}{max} \left[w_j \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right] \tag{11}$$

Step 2: VIKOR Compromise Index

The compromise ranking index Q_i is calculated as:

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \tag{12}$$

where:

$S^* = min_i S_i$, $S^- = max_i S_i$

$R^* = min_i R_i$, $R^- = max_i R_i$

v represents the weight of group utility (taken as $v = 0.5$ for this study)

The Pareto solution with minimum Q_i, satisfying acceptable advantage and stability conditions, is selected as the **baseline execution plan**.

Dynamic Many-Objective Optimization Model for project control

To address execution-stage uncertainty, a Dynamic MaOO re-optimization model is introduced. The dynamic MaOO model extends the static planning optimization into the execution phase by incorporating real-time project progress.

At each decision point

- Lock the completed activities and remove from the decision space.
- Partially completed activities contribute only to the remaining work.
- Remaining activities are re-optimized using OBNSGA-III.
- Normalization of new Pareto solutions is done along with the planned solution
- In the normalized plane, calculated the distance between re-optimized solutions.
- The solution having minimum deviation from the planned solution is selected to continue the execution.

This mechanism ensures adaptability while preserving consistency with the original compromise plan.

During project execution, the model incorporates actual obtained objective values for completed activities. If deviations are observed between planned and achieved values, the optimization is re-executed using the updated data. The model then recommends revised execution modes for the remaining activities, ensuring alignment with the original project objectives with minimum deviation from the planned objective values. The model works on OBNSGA-III algorithm with updated input data obtained during execution.

Model Flow Chart is shown in Figure-1.

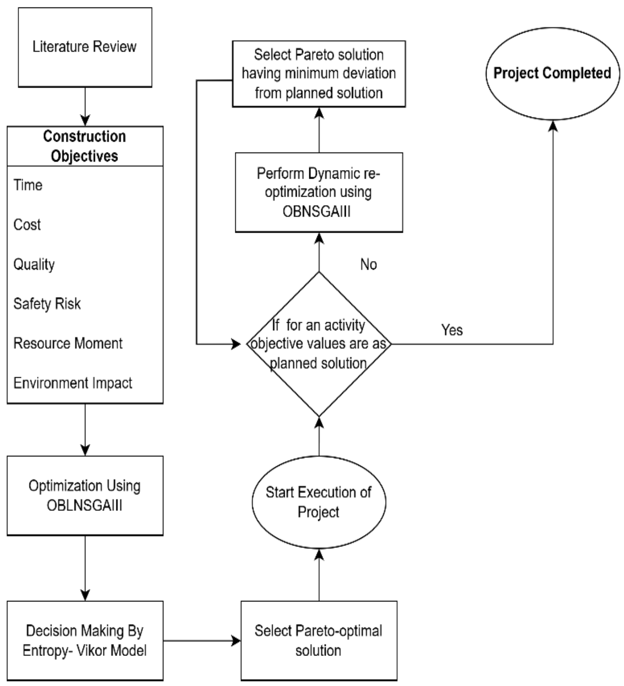

Figure 1: Flow Chart of Proposed Model

Case Study and Result

The case study involves 25 activities with various execution modes, yielding a combinatorial search space of over 53 million alternatives related to a construction project. Optimization of this project is done on OBNSGAIII model, and 78 Nos of pareto-optimal solutions are obtained. The Multi-Objective Trade-off based on normalized values is shown below as Figure 2.

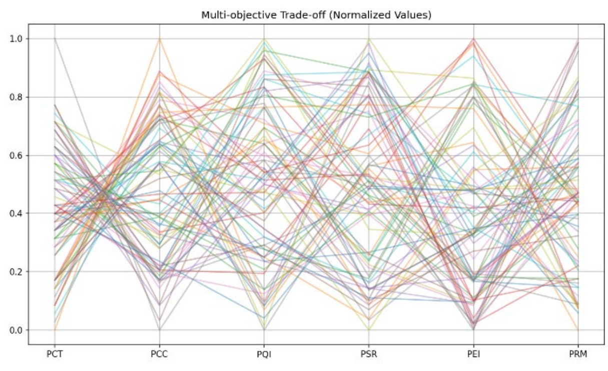

Figure 2 : Multi-Objective Trade-off based on normalized values

After this the multi-criteria decision making was done based on Entropy based VIKOR model to select a solution set for the project execution.

Results of Entropy weight calculated from model for objectives are: PCT: 0.166, PCC: 0.134, PQI: 0.177, PSR: 0.210, PEI:0.160, PRM:0.153. And selected solution set after Entropy VIKOR model- Pareto Index-23, selected modes of execution for 25 activities (A1-A2-…-A25) are: 1-2-1-1-1-1-3-3-2-3-3-1-1-2-1-2-2-1-2-2-1-1-2-1-1 and project objective values are: PCT: 243 days, PCC: 723900 Rs., PQI: 0.86, PSR: 75.22, PEI: 70.92, PRM 1855.

This Pareto solution is used for execution of project. After completion of first two activities, it is found that objective values are deviated as per planned due to resource unavailability at project site. So, dynamic re-optimization model is used to re-optimize the project and 38 pareto solutions are found. The solution having minimum deviation from planned solution, modes are used for re-execution of project.

The achieved values of objectives and deviation from the planned solution are shown in Table-1.

Table 1: Planned vs Achieved Project Performance

Objective	Planned	Achieved	Deviation (%)
PCT	243	230	-5.35
PCC	723900	815700	12.68
PQI	0.8564	0.8676	1.31
PSR	75.22	74.435	-1.04
PEI	70.92	82.295	16.04
PRM	1855	1995	7.55

The dynamic re-optimization results illustrate how planning decisions can be revised in response to resource unavailability without discarding the original planning rationale. This model is similar to lean construction thinking, which emphasizes maintaining plan reliability while accommodating inevitable execution variability through continuous control rather than complete re-planning.

Conclusion and Future Work

This study proposed an integrated many-objective framework for construction planning and control by combining OBNSGA-III optimization, Entropy–VIKOR decision making, and a dynamic re-optimization mechanism. Unlike most existing studies that limit analysis to five objectives and static planning, the proposed approach explicitly considers six project-level objectives—time, cost, quality, safety risk, environmental impact, and resource moment thereby providing a more complete representation of construction production behaviour.

From the case study we can say that OBNSGA-III can effectively manage a large combinatorial decision space and generate a diverse set of Pareto-optimal solutions. However, the results also confirmed that Pareto optimization alone is insufficient for practical decision-making. The Entropy–VIKOR model enabled objective selection of a balanced compromise solution without relying on subjective weighting, producing an execution plan with acceptable performance across all six objectives.

The dynamic re-optimization results further showed that construction plans must adapt during execution. When deviations occurred due to resource unavailability, the proposed dynamic model successfully re-optimized the remaining activities and identified revised execution modes with minimum deviation from the original plan. This demonstrates that many-objective optimization can function as a control-oriented decision-support tool, rather than a one-time planning exercise.

The explicit inclusion of resource moment as a sixth objective proved critical, as it revealed differences in execution stability that were not visible through time–cost–quality–safety–environment trade-offs alone. Overall, we can say that the proposed framework supports more reliable planning and controlled adaptation during execution of project, and the framework aligns well with lean construction principles.

From a lean construction point of view, the proposed framework contributes to planning–control integration by enabling structured adaptation of production decisions in response to variability, supporting more reliable execution without relying on rigid or static plans.

Future work can also be done on real-time data integration through BIM-enabled progress tracking and site data acquisition systems. By linking this proposed optimization model with live data streams would allow automatic updating of activity status, resource usage, and performance indicators, transforming the framework into a decision-support system that operates throughout the project lifecycle.

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