
A Meta-Model based-Simulation Optimization approach for controlling rework delay duration in construction: An Intelligent Metamodeling Approach

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Abstract

Background and Objective: Rework is one of the main contributors to cost overruns, delays, and reduced productivity in construction projects. Since this phenomenon has a nonlinear and stochastic nature, conventional analytical methods do not provide sufficient capability for modeling and controlling it. The objective of this study is to propose an integrated metamodel-based simulation-optimization framework to control the duration of rework-induced delays in construction projects. Research Method: This study employs a hybrid approach combining mathematical modeling, discrete-event simulation, design of experiments (DOE), central composite design (CCD), regression-based metamodeling, and heuristic optimization. The Modified NBI method is also used to address the multi-objective optimization problem. The research data were collected from a five-scenario building project in Tehran as well as 55 construction projects in the Middle East during 2015–2020. Findings: The results indicate that factors such as rework frequency and duration, workforce experience, conflicts among project stakeholders, payment delays, and political conditions are among the most influential contributors to rework. Moreover, the proposed metamodel transforms the simulation objective function from a black-box representation into a more explicit and solvable form, thereby reducing the computational burden of the optimization process. Conclusion: The findings suggest that integrating simulation, metamodeling, and optimization can provide an effective approach for controlling and reducing rework-related delays in construction projects. This framework improves decision-making accuracy while enabling the identification of optimal and Pareto solutions at a lower computational cost.

Keywords: Discrete Event Simulation, Simulation-based Optimization, Metamodelling, Meta-Model

Paper Type: Original Research

1. Introduction

In the modern construction industry, characterized by high levels of uncertainty and structural complexity, rework has emerged as a critical bottleneck, severely undermining project performance through cost overruns and significant schedule slippages (Alipour et al., 2026). While traditional management approaches often treat rework as a static consequence of errors, its impact on delay duration is a dynamic, non-linear phenomenon driven by stochastic variables such as rework frequency, timing, and resource volatility. Despite extensive literature identifying the causes of rework, there remains a substantial research gap in developing robust, quantitative frameworks capable of not only simulating these complex behaviors but also optimizing control strategies in real-time. To address this, an integrated meta-model based simulation-optimization approach is essential, providing an intelligent, computationally efficient surrogate for traditional simulation that enables project managers to minimize rework-induced delays and stabilize project delivery under uncertain conditions (Abolghasemian et al., 2026). In recent years, the construction industry, as one of the most important economic and infrastructural sectors of countries, has faced numerous challenges such as reduced productivity, increased costs, and delays in project execution (Yap et al., 2024). One of the major factors contributing to reduced productivity in construction projects is the phenomenon of rework. Rework refers to activities that must be performed again due to execution errors, design deficiencies, poor project management, or lack of coordination among different project participants (Love et al., 2021). This phenomenon not only imposes additional costs but also increases project duration, leads to resource waste, reduces the final quality of the project, and causes dissatisfaction among stakeholders (Sadeghi Sabzevari et al., 2026). Studies

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indicate that in some construction projects, the costs associated with rework may account for up to about 10 percent of the total project cost, and a significant portion of construction activities are directly or indirectly affected by it (Abolghasemian et al., 2021). On the other hand, construction processes are inherently associated with various uncertainties. Factors such as adverse weather conditions, fluctuations in material supply, shortages of skilled labor, lack of coordination among project stakeholders, design changes, and managerial constraints can lead to interruptions in construction activities and consequently increase the likelihood of rework (Khajvandsany et al., 2025). These interruptions ultimately cause deviations from the project schedule and extend the overall project duration. Under such conditions, effective management of rework and control of the delays caused by it have become major challenges for project managers (Abolghasemian et al., 2022). Given the complexity and dynamic nature of construction processes, analyzing and evaluating the impacts of rework on project performance using traditional analytical methods is difficult (Al-Attabi et al., 2025). In this context, simulation is recognized as a powerful tool for modeling the behavior of complex systems, enabling the examination of system performance under different conditions and the analysis of the effects of various variables on system outputs (Huang et al., 2024). Through simulation, the effects of different rework parameters such as the time of occurrence, frequency of occurrence, and duration of rework can be examined with respect to project performance indicators such as total project duration, costs, and productivity (Hemmati et al., 2024). However, the complexity and uncertainty of construction processes make it difficult to quantify and control the duration of delays caused by rework using traditional analytical methods. However, using simulation alone is not sufficient for identifying the best decisions, because obtaining the optimal values of decision parameters typically requires running a large number of simulation experiments, which can be very time-consuming and costly (Alshihiri et al., 2022). In such cases, combining optimization methods with simulation models can provide an effective approach for determining optimal values of decision variables and improving system performance. In this approach, surrogate or approximation models are usually used to represent the behavior of the simulation model, enabling the search for optimal solutions to be conducted more efficiently (Khan et al., 2025). Although previous studies have examined the causes and impacts of rework, few have addressed the quantitative modeling and optimization of rework-induced delay duration within an integrated simulation-optimization framework. The proposed framework seeks to determine the optimal values of rework timing, frequency, and duration in order to minimize project delay and improve construction performance. This research gap highlights the importance of developing models that can simultaneously simulate the behavior of construction systems and determine the optimal values of parameters related to rework. Accordingly, current study aims to develop an integrated simulation-optimization approach for controlling the duration of delays caused by rework in construction processes. In this regard, the behavior of the construction process and the rework phenomenon are first analyzed through a simulation model. To overcome the computational burden of repeated simulation runs during optimization, a surrogate (metamodel) is needed as an efficient approximation of the simulation model. Then, by developing a surrogate model as a substitute for the simulation model, the optimization of parameters related to rework becomes possible. The aim of this approach is to determine the optimal values of variables such as the timing of rework occurrence, its frequency, and its duration in order to reduce project delays and improve the overall performance of construction processes. The results of this study can serve as a decision-support tool for project managers to better control construction operations, reduce resource waste, and enhance productivity in construction projects. Therefore, current study contributes by integrating mathematical modeling, discrete-event simulation, and metamodel-based optimization into a unified framework for managing rework-induced delays.

2. Literature Review

In the literature on construction projects, numerous studies have examined the key factors and risks causing project delays. Al-Bataineh et al. (2012) identified scope changes, delays in progress payments, weak coordination among project stakeholders, material price fluctuations, adverse weather conditions, and economic issues as major causes of delays. Hunter et al. (2013) highlighted low-price bidding, design changes, financial problems, delayed payments to contractors, delays in information transfer, and rejection of completed work by supervision authorities. Amaran et al. (2015) emphasized rework during execution, design changes by the client and consultant, labor shortages, waiting for work crews, and price fluctuations. Similarly, Liu and Yang (2016) pointed to the inability of key stakeholders, including clients, consultants, designers, contractors, and supervisors. Anil and Danielraj (2016) compared delay causes across countries and found that poor planning and scheduling dominate in Australia, payment delays and unrealistic cost estimates in Ghana, and weak contractor planning and site management in Malaysia. Other studies identified additional factors such as delayed decision-making, inconsistencies between drawings, major design changes during construction (Zeinali et al., 2015), insufficient workforce skills, poor contractor planning, delayed payments, and limited consultant experience (Tsai et al., 2017). Enshasi et al. (2017) further emphasized lack of knowledge among project stakeholders, weak business decisions, poor risk management, and weak procurement management. More recently, Love et al. (2021) proposed a neural-network-based approach

for predicting delays in prefabricated construction projects by considering risk factors. Several studies have also focused on rework, productivity, and advanced analytical approaches in construction. Abolghasemian et al. (2021) analyzed the impact of rework delays using a hybrid discrete-event simulation and computational modeling approach. Alshihri et al. (2023) investigated the critical risk factors contributing to cost and time overruns in government-funded projects utilizing standard procurement contracts. Through a survey of industry experts and the application of the Relative Importance Index (RII), the study identified key drivers of project failure, notably contractor financial instability, payment delays by owners, and the 'lowest bidder' procurement strategy. The findings emphasize that mitigating client and contractor-related risks is essential for the sustainable delivery of infrastructure projects within the region. Huang et al. (2024) integrated BIM and backpropagation neural networks to analyze risk management throughout the life cycle of large public buildings. Yap et al. (2024) investigated work interruptions during the installation of precast concrete columns in a logistics center project. Abdolghasemian et al. (2024) proposed a systematic framework for evaluating and managing delay risks in construction projects using the Delphi method, scenario analysis, and PERT techniques in Iranian highway projects. In another major research stream related to simulation-based mathematical modeling, several studies have developed surrogate models and simulation optimization techniques. Abdul Matin Khan et al. (2025) developed a plugin that facilitates simultaneous assessment of cost, energy consumption, and embodied carbon. Their findings demonstrated that this digital integration can yield a 10% reduction in project costs and a 15% decrease in embodied carbon emissions through data-driven material selection. Precious (2025) identified a counterintuitive relationship, characterized by 'crisis-driven acceleration,' where cost overruns were positively associated with improved schedule performance. This suggests that in high-visibility projects, additional resources are often deployed to mitigate delays, effectively prioritizing schedule adherence over budgetary constraints. Attabi (2025) categorized 59% of these factors as major, with incompetent contractors and owner-related issues identified as the most significant drivers of delay. These findings underscore the critical role of stakeholder performance in volatile environments, providing a prioritization framework for mitigation strategies. Cho et al. (2026) proposed a proactive framework leveraging Pretrained Language Models (PLMs) and Machine Learning (ML). By integrating automated Probability-Impact Matrices (PIM) with predictive modeling, the study enhances delay forecasting accuracy. Furthermore, the incorporation of SHAP (SHapley Additive exPlanations) ensures model interpretability, marking a significant advancement in data-driven risk management within the Construction 4.0 paradigm. Also, the first attempts to develop simulation model optimization using metamodeling were carried out by various researchers. Dingiz et al. (2015) proposed a regression-based surrogate model to determine optimal batch sizes in MRP and JIT systems. Kleijnen (2013) used experimental design and response surface methodology (RSM) for simulation optimization and multi-objective problems. Subsequent studies applied similar approaches in different domains, including production systems, transportation, healthcare, and mining operations (Dingiz, 2009; Yalçınkaya and Bayhan, 2009; Dingiz et al., 2015; Zainali et al., 2016). Later works expanded these approaches by integrating simulation, optimization, and metaheuristic methods such as OptQuest and NBI for complex decision-making problems (Abdolghasemi et al., 2018, 2020, 2022). More recent applications include healthcare resource optimization during the COVID 19 pandemic (Jahangiri et al., 2023) and production line balancing in petrochemical industries using simulation optimization (Hemmati et al., 2024). In a related study, Paape et al. (2025) an approach based on a genetic algorithm (GA) and discrete-event simulation (DES) was proposed to address the research gap in production system topology optimization. In this study, a neural network was employed as a surrogate model for simulation to mitigate computational costs. The findings indicated that while both approaches were effective in identifying optimal solutions, the implementation of the surrogate model significantly enhanced scalability and reduced computational overhead. In another study, Nikoukar and Tavakolan (2026) a simulation-based optimization approach was proposed to enhance site layout planning and resource allocation. By integrating a Genetic Algorithm (GA) with Discrete Event Simulation (DES), the research optimized tower crane placement, depot locations, and supplier selection for a real-world steel structure project. The framework demonstrated significant potential in minimizing costs and improving productivity by accounting for project boundaries and transportation logistics, moving beyond the limitations of traditional, site-confined mathematical models. Despite the extensive body of literature exploring the causes and consequences of rework in construction projects, a significant research gap persists between the qualitative identification of rework drivers and the development of a quantitative, dynamic, and actionable framework for controlling rework-induced delay durations. Traditional analytical approaches remain predominantly static and linear, failing to capture the non-linear and stochastic nature of rework under uncertainties such as resource volatility, design changes, and operational disruptions. Furthermore, while discrete-event simulation offers a powerful means to model these complexities, relying solely on simulation to identify optimal decisions is computationally prohibitive due to the need for exhaustive scenario testing. Consequently, there is a critical lack of an integrated simulation-based optimization framework based on metamodels (surrogate models) that can mitigate the computational burden of simulation while accurately optimizing key rework parameters such as timing, frequency, and duration to minimize overall project delays. This underscores the necessity for an intelligent, metamodel-driven approach to stabilize project delivery and effectively control the duration of rework-induced delays in complex construction environments.

3. Methodology

The methodology of this study is based on a hybrid approach that integrates mathematical modeling, discrete-event simulation, and heuristic optimization. The research process is conducted through the following four systematic steps:

Step 1: System Identification and Data Collection:

First, the construction processes (specifically the foundation phase) were analyzed to identify “rework-prone” activities. Key performance metrics such as rework frequency, duration, and call-back timeframes were defined. Historical data and expert opinions were used to determine the statistical distributions of work processes (e.g., the Erlang distribution for the foundation process). Finally, the collected data were analyzed using the Z-number ranking method. This approach enables the prioritization of factors based on their cumulative scores. A Z-number is an ordered pair of fuzzy numbers denoted as $Z=(A,B)$. The first component, A, represents the fuzzy constraint on the values that the variable X can assume. The second component, B, indicates the reliability (or certainty) of the first component. A and B are typically described using linguistic terms and are represented as fuzzy sets, such as triangular or trapezoidal fuzzy numbers. In many practical applications, the ranking of fuzzy numbers serves as a critical component of decision-making processes. In this study, the Z-number ranking method is presented to prioritize the factors influencing rework in construction. This method is based on the internal structure of Artificial Neural Networks (ANN), which consists of inputs, weights, and transfer functions (both linear and non-linear). A Z-number is introduced in association with an uncertain variable x. Specifically, a Z-number is a pair of fuzzy numbers (A,B) where A is a fuzzy subset of the constraints on the values x can take, and B is a fuzzy subset representing the reliability measure of component A.

Step 2: Discrete-Event Simulation (DES) Modeling:

A simulation model was developed using Arena 14.0 software to replicate the workflow variability and the impact of rework cycles. The model was designed to simulate 12 distinct “What-if” scenarios, varying the frequency and duration of rework across three call-back timeframes (Early, On-time, and Late). A warm-up period was defined to ensure the system reached a steady state before data collection.

To guarantee the reproducibility and statistical validity of the simulation outputs, the simulation run parameters were rigorously specified. A warm-up period of 4 operating days was determined using Welch’s graphical moving-average approach to eliminate initialization bias. Each replication was run for a duration of one month (24 working days). To achieve statistically robust estimates, 10 independent replications were performed, and the half-width analysis confirmed that the 95% confidence intervals ($\alpha=0.05$) for the key performance metrics fell within an acceptable relative error margin ($< 5\%$).

Step 3: Simulation-Based Optimization:

To minimize rework-related costs and durations, the OptQuest® optimization engine was integrated with the Arena model. This phase involved defining decision variables (e.g., workforce experience, stakeholder conflict) and establishing their upper and lower bounds. The optimization process utilized Scatter Search, Tabu Search, and Neural Networks to identify the most cost-effective configuration of project variables. OptQuest Optimization for Rework Mitigation algorithm is following as (Abolghasemian et al., 2020):

```
BEGIN
/* STEP 1: INITIALIZATION */
Identify Decision Variables (X): {Workforce Experience, Stakeholder Conflict, Political Status, etc.}
Set Constraints: Define Lower and Upper Bounds for each X_i
Set Objective Function: Minimize Z = Total_System_Cost(X)
Initialize Scatter Search: Create an initial Reference Set of high-quality solutions
Initialize Tabu Search: Setup memory structures to record visited regions
Initialize Neural Network (NN): Setup the meta-model to predict simulation outcomes
Set Termination_Criteria: (e.g., Max_Iterations = 100 or Improvement_Threshold < epsilon)
Set Best_Cost = Infinity
Iteration_Counter = 0
/* STEP 2: OPTIMIZATION LOOP */
WHILE (Iteration_Counter < Max_Iterations AND Termination_Criteria NOT met) DO
  // Generate candidate solution using Scatter Search (Combination Method)
  Candidate_X = Generate_Candidate_Solution(Reference_Set)
  // Ensure the candidate respects all linear/non-linear constraints
  IF (Is_Feasible(Candidate_X)) THEN
    /* STEP 3: NEURAL NETWORK PRE-SCREENING */
    // Predict performance to avoid redundant simulation runs
    Predicted_Performance = Neural_Network_Predict(Candidate_X)
    IF (Predicted_Performance is Promising) THEN
      /* STEP 4: SIMULATION EXECUTION (e.g., Calling Arena 14.0) */
      Run_Simulation_Model(Candidate_X)
      Actual_Cost = Extract_Simulation_Output("Total_System_Cost")
      // Update Tabu Search memory to guide the search away from local optima
      Update_Tabu_List(Candidate_X)
      /* STEP 5: PERFORMANCE EVALUATION & UPDATE */
      IF (Actual_Cost < Best_Cost) THEN
        Best_Cost = Actual_Cost
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        Best_X = Candidate_X
        Update_Reference_Set(Candidate_X) // Update Scatter Search population
    END IF
    // Re-train Neural Network with the new data point to increase accuracy
    Update_Neural_Network_Weights(Candidate_X, Actual_Cost)
    END IF
    END IF
    Iteration_Counter = Iteration_Counter + 1
END WHILE
/* STEP 6: OUTPUT RESULTS */
PRINT "Optimization Complete"
RETURN Best_X, Best_Cost
END
Finish

```

Step 4: Validation and Comparative Analysis:

Finally, the results obtained from the simulation-based optimization were validated against computational results. A comparative analysis was performed between the “Current State” and the “Optimal State” to quantify the reduction in total project costs and the improvement in completion timelines. Figure 1 illustrates the analytical process structure for optimization based on simulation modeling, OptQuest, and the implementation of the optimization coding process in MATLAB.



Figure 1. Framework of simulation-based optimization software

Step 5: Simulation-based optimization approach

Simulation-based optimization method generally applicable to simulation-optimization problems. In this approach, the factors under the decision-maker's control (such as the definition of decision variable bounds) and uncontrollable factors (such as the response level and other deterministic constraints) are first specified within the model. The decision factors are at the disposal of the decision-maker, and an interval between the lower and upper bounds of the problem's decision variables is selected to form the Design of Experiments (DOE). Additionally, environmental factors vary randomly within a specified range around their hypothetical nominal values. The core idea of this method is to estimate an optimal production combination for the decision variables by selecting experimental points, while also explicitly identifying the uncertain nature of the objective function. In the first phase of this method, the optimal production control of the current state is considered. In this phase, the near-optimal values of the controllable variables in the simulation model are calculated based on existing demand and the integrated capacity of the system. The process architecture of the first phase mechanism is illustrated in Figure 2.

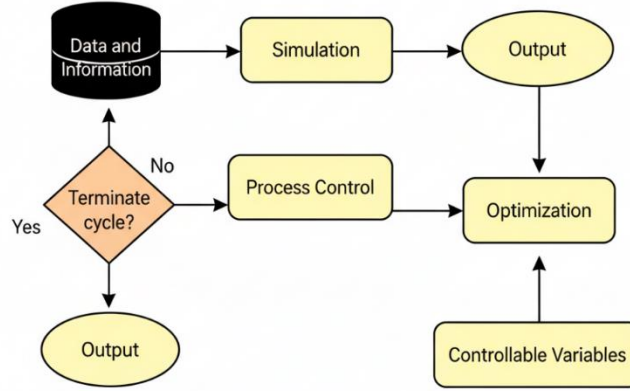


Figure 2. Framework of simulation-based optimization process

Simulation-based optimization framework is to establish a deterministic model that can satisfy the rework delay, considering the stochastic (non-deterministic) nature of simulation models. According to Abolghasemian et al. (2020), a metamodel-based (surrogate-based) optimization approach comprises the following key elements: Identifying the Metamodel Form: Selecting the mathematical form of the metamodel to estimate the objective function is highly flexible and problem-dependent.

Design of Experiments (DOE): The metamodel function is characterized through a design of experiments, which determines the input configurations for the simulation model.

Metamodel Fitting and Validation: First, the simulation model is executed to obtain responses for model fitting. Then, parameter values are estimated from the gathered data using the least squares method. Finally, the model's validity must be verified using standard validation techniques.

Optimization: Various mathematical and heuristic optimization methods exist to optimize decision variables, such as Simplex, Genetic Algorithm (GA), Simulated Annealing (SA), and Tabu Search (TS).

The most significant outcome of current step of the proposed simulation-based optimization framework is determining the explicit mathematical form of the objective function in Step 3, transitioning it from a black-box to a white-box state. Consequently, in current step of the proposed methodology, since the functional form of the objective function is unknown, it is first estimated using a regression metamodel. A Central Composite Design (CCD) is employed to estimate the objective function. Next, the simulation model is executed for r replications at each experimental point, and the resulting outputs are denoted as R_{ij} for $i = 1, 2, 3, \dots, n$ and $j = 1, 2, 3, \dots, r$. The average response for the simulated design points is calculated as follows:

$$\bar{R}_i = \frac{1}{r} \sum_{j=1}^r R_{ij}, \quad i = 1, 2, 3, \dots, n \quad (1)$$

The regression metamodel is fitted to the estimated average responses and is subsequently validated using various statistical analyses. The general mathematical structure of the optimization problem in the second phase is formulated as shown in Equations (2):

$$\begin{aligned}
 (2) \quad & \min z_1 = f_j(x_1, x_2, \dots, x_n), & j = 2, 3, \dots, r \\
 & \min z_2 = f_j(x_1, x_2, \dots, x_n), & j = 2, 3, \dots, r \\
 & \vdots \\
 & \min z_n = f_j(x_1, x_2, \dots, x_n), & j = 2, 3, \dots, r \\
 & s. t \\
 & g_i(x) \leq 0, & i = 1, 2, \dots, m \\
 & x_i^l \leq x_i \leq x_i^u, & i = 1, \dots, n \\
 & x_i \in \text{integer}
 \end{aligned}$$

In Equation (2), z represents the objective function of the response surface variable, and $f_j(x_1, x_2, \dots, x_n)$ denotes the j -th estimated objective function. Moreover, $g_i(x)$ represents the deterministic constraint functions, and x_i^l and x_i^u denote the lower and upper bounds of the i -th decision variable, respectively.

3.1 Solution Approach: Modified NBI

The modified NBI method is designed to identify the Pareto frontier in multi-objective optimization problems with continuous or piecewise-continuous boundaries. Its procedure consists of two main components: applying the modified CHIM+ technique within the optimization model and controlling the number of optimization iterations. Before implementation, the objective functions are normalized to the interval $[0, 1]$. If an objective function is unbounded or its upper limit is unknown, an appropriate bound can be specified by the user. The optimization problem may be solved using a quasi-Newton method, which generates a local optimum without relying on a population of candidate solutions. Unlike stochastic techniques such as genetic algorithms which require several

parameters and often need multiple runs due to their random nature the modified NBI approach requires only one parameter to determine the number of Pareto points. Moreover, it provides consistent results across repeated executions. The general procedure of the proposed method is as follows:

Input: Number of significant digits and initial points

Output: Set of non-dominated solutions

1. Normalize the objective functions.
2. Generate initial Pareto points.
3. Initialize the objective-function optimization process.
4. Construct an accurate Pareto set.
5. Fix the objective-function values.
6. Eliminate Pareto-dominated solutions.
7. Determine the final optimal solutions.

4. Findings and Discussion

To ensure data transparency, the input parameters were categorized into two distinct sources: Primary Field Data and Secondary Benchmark Data. The Primary Field Data (e.g., activity durations, daily operational logs, unit floor areas, and labor assignments) were collected directly from the residential project in Fereshteh, Tehran, through site observations and contractor records. Conversely, the Secondary Benchmark Data, specifically rework factor weights and probabilistic ranges (e.g., impact of payment delays or workforce experience on cost/time), were derived from the empirical dataset established by Mahamid (2023) regarding 55 construction projects. Table 1 outlines the sources for each input factor. In current study, the factors influencing rework in residential buildings are identified. For this purpose, numerical data from a large-scale construction company in Tehran were used. The collected information pertains to a five-scenario building comprising 10 residential units with floor areas ranging from 100 to 120 square meters in the Fereshteh neighborhood of Tehran. In addition, data from 55 construction projects built in the Middle East between 2015 and 2020 (Mahamid, 2023) were collected. These data include information on the cost of rework as a share of total project cost overrun. Based on the literature review, six factors were identified as causes of rework in projects: rework frequency and rework duration (Abolghasemian et al., 2021), workforce experience, conflicts among project participants, payment delays, and political conditions (Mahamid, 2023). The initial data are presented in Table 1.

Table 1. Factors associated with rework in construction projects

Factor	Minimum Value	Mean Value	Maximum Value
Rework frequency (Abolghasemian et al., 2021)	7	124	28
Rework duration (Abolghasemian et al., 2021)	1	2	4
Workforce experience (Mahamid, 2023)	1.8	17.5	59.2
Conflict among project participants (Mahamid, 2023)	3.8	13.7	55.2
Payment delay (Mahamid, 2023)	5.6	13.7	52.3
Political status (Mahamid, 2023)	6.4	7.5	34.7

Rework patterns directly impact project duration; their frequency and duration (ranging from weekly short interruptions to monthly prolonged rework) introduce proportional schedule delays. A primary driver of rework, poor quality, and material waste is the shortage of qualified personnel, which stems from regional economic instability and uncompetitive wages in Palestine, prompting skilled labor emigration (confirmed by 77% of respondents as a major source of waste). Although repetitive rework may offer minor learning-curve advantages, its net effect remains detrimental to project budgets. Inter-stakeholder friction also severely undermines project efficiency. Poor collaboration and misaligned coordination across project teams lead to suboptimal planning and resource mismanagement, which 69% of participants identified as a critical cause of cost escalations and waste. Concurrently, cash-flow bottlenecks caused by delayed disbursements from project owners or contractors diminish labor productivity, disrupt supply procurement, and worsen material loss, as highlighted by 66% of surveyed professionals. At the macro level, geopolitical unrest and logistical impediments in Palestine further exacerbate construction inefficiencies. Physical restrictions, such as checkpoints and regional closures in the West Bank, impede the transit of manpower, materials, and machinery. These constraints, coupled with public-sector budgetary deficits, intensify contractor liquidity shortages, yielding substantial progress delays and inflated expenses (supported by 59% of respondents). To prioritize these critical factors, a Z-number algorithm was executed via Microsoft Excel 2016. The initial layer of the artificial neural network was established using a uniform parameter set $B=(0,1,1,0)$ across all variables (Table 2), while the computational procedures for the subsequent neural network layer are detailed in Table 3.

Table 2. First-layer formation steps for all variables

Fuzzy Numbers	First-Layer Input Introduction	First-Layer Bias Term Formation	First-Layer Neuron Formation	ANN First-Layer Output
(0, 1, 1, 0)	0.500	0.333	1.077	0.792

According to Table 2, the fuzzy numbers B, namely (0, 1, 1, 0), represent the confidence scale of component A. These fuzzy numbers are introduced as input to the first layer of the neural network using the relevant equation $\bar{x}_{\beta_i} = \frac{(b_1 + b_2 + b_3 + b_4)}{4}$. The deviation term of the first layer of the neural network is calculated according to the specified

instruction $b\beta_i = \frac{\sum_{i=1}^4 (b_i - \bar{x}_{\beta_i})^2}{3}$, and the formation of the first-layer neuron is carried out accordingly $n = \bar{x}_{\beta_i} W_{\beta_i} + b_{\beta_i}$. The output of the first layer of the neural network is the weight used as the second-layer weight $\alpha B = T_H(n)$.

Table 3. Second-layer formation steps for the variables

Variables	Fuzzy Numbers	Normalized Fuzzy Numbers	Second-Layer Input Introduction	First-Step Output (Weight)	Second-Layer Bias Term Formation	Second-Layer Neuron Formation
Rework Frequency (Z1)	(7, 14, 21, 28)	(0.25, 0.5, 0.75, 1)	0.625	0.792	21.47619	21.97429
Rework Duration (Z2)	(1, 2, 3, 4)	(0.25, 0.5, 0.75, 1)	0.625	0.792	2.520747	3.015881
Workforce Experience (Z3)	(1.8, 17.5, 21.5, 59.2)	(0.03, 0.29, 0.36, 1)	0.422	0.792	37.37385	37.71830
Project Participants Conflict (Z4)	(3.8, 13.7, 27.3, 55.2)	(0.07, 0.25, 0.49, 1)	0.452	0.792	36.07724	36.43603
Payment Delay (Z5)	(5.6, 13.7, 28.4, 52.3)	(0.11, 0.26, 0.54, 1)	0.478	0.792	34.95813	35.33681
Political Status (Z6)	(6.4, 7.5, 34.7, 51.4)	(0.12, 0.15, 0.68, 1)	0.486	0.792	35.80936	36.19467

According to Table 3, for example, the fuzzy number [7, 14, 21, 28] corresponding to the rework frequency variable is normalized using the relevant equation $C = \max_i(a_i \cdot 1)$, $a_i^* = \frac{a_i}{C}$, $w_{\bar{A}_i} \in [0,1]$ resulting in (0.25, 0.5, 0.75, 1). Based on the corresponding equation $sum(a_i^*)/4$, the second-layer input is equal to 0.625. By applying the absolute value of the first-stage output $|\alpha_\beta|$, the second-layer weight of the neural network is determined, which in this case is 0.792214. The deviation term of the second layer of the neural network is obtained as 21.47619 according to the

relevant equation $b_{A^*} = \sqrt{\frac{\sum_{i=1}^4 (a_i - \bar{x}_{A^*})^2}{3}}$, and the formation of the second-layer neuron yields 21.97429 using equation $n = (\bar{x}_{A^*} \times w_A) + b_{A_i} = (\bar{x}_{A^*} \times |\alpha_b|) + b_{A^*}$. The output of the neural network is considered as the Z-number rank.

$Ran\ k(Z1) = 21.97429$

$Ran\ k(Z2) = 3.015881$

$Ran\ k(Z3) = 37.7183$

$Ran\ k(Z4) = 36.43603$

$Ran\ k(Z5) = 35.33681$

$Ran\ k(Z6) = 36.19467$

The larger the Rank number, the higher its rank. Therefore, Z3 is greater than Z4, Z4 is greater than Z6, Z6 is greater than Z5 and Z5 is greater than Z1 and Z1 is greater than Z2. In other words, workforce experience, conflict among project participants, political conditions, and payment delays are respectively the most influential factors affecting rework. The results show that the higher the average of the numbers used, the higher the rank will be.

4.1 Development of the discrete event simulation (DES) model

Due to comprehensive data availability, the residential housing sector serves as the empirical context of this dissertation. Data were acquired from an active construction enterprise for a five-scenario development containing ten residential units (100–120 m² each). The operational workflow was formulated as a network of interdependent predecessor and successor tasks, reflecting contractor interactions on-site. In this setup, seamless project progression requires each trade to execute defect-free tasks on schedule before handing over to subsequent teams. Any operational defect mandates rework by the responsible contractor, causing delays and cascading queue formations due to trade interdependencies. Consequently, the simulation framework captures these stochastic cycles and operational variations. For detailed investigation, the analysis focuses specifically on the building foundation phase. This activity, characterized by an Erlang distribution (19.5+Erlang [0.792,2]) was modeled using queuing theory principles; the corresponding computational outputs are summarized in Table 4.

Table 4. Computational Modeling Results for the Foundation Process

Parameter	Very Frequent - Very Short	Frequent - Short	Infrequent - Long	Very Infrequent - Very Long
Rework Duration	Exp,4.5	Exp,5.5	Exp,6.5	Exp,8
Availability Level	97.5	97.5	97.5	97.5
Throughput	0.031	0.031	0.031	0.031
Queue Length	0.051	0.072	0.223	0.154
Queue Clearance Rate	0.005	0.005	0.005	0.005
Queue Clearance Time	7.89	14.55	22.5	28.96

Computational modeling of rework-prone activities demonstrates that both rework frequency and duration substantially govern operational performance. Contrary to typical managerial preferences for avoiding frequent interruptions, the analysis reveals that high-frequency, short-duration rework outperforms long, infrequent rework cycles. In foundation operations, shorter rework intervals minimize queue accumulation and clearance times, whereas prolonged and rare rework significantly inflates work backlogs. Thus, mitigating workflow variability across interdependent contractors curtails total project duration. Because analytical methods cannot readily handle the complexity of metrics like throughput (completed units), work-in-progress (WIP), and lead times, a discrete-event simulation model was constructed in Arena 14 (Figure 2). The system was simulated over 1,500 operating days (with a 4-day warm-up period to ensure steady-state conditions) and successfully validated against empirical records, showing no statistically significant discrepancies. In this workflow, task approval via quality inspection allows subsequent trades to proceed; otherwise, the defective task triggers a contractor call-back. To evaluate “what-if” scenarios, 12 experimental configurations were tested by crossing three call-back horizons with four rework profiles (Table 5). The findings confirm that early call-backs markedly enhance project productivity maximizing completed units while minimizing WIP and completion times. Consequently, the optimal configuration combined very frequent, brief rework with immediate call-backs (Experiment 9), whereas the least effective setup involved infrequent, prolonged rework coupled with delayed call-backs (Experiment 8).

Table 5. DES results

Row	Rework Call-back Timeframe	Rework Frequency	Rework Duration	Number of Completed Buildings	Number of Buildings under Construction (WIP)	Completion Duration (Days)
1	On-time	Very Frequent	Very Short	49	33	418
2	On-time	Frequent	Short	44	36	438
3	On-time	Infrequent	Long	42	38	451
4	On-time	Very Infrequent	Very Long	40	40	471
5	Late	Very Frequent	Very Short	39	37	441
6	Late	Frequent	Short	35	39	462
7	Late	Infrequent	Long	32	42	479
8	Late	Very Infrequent	Very Long	29	44	498
9	Early	Very Frequent	Very Short	63	27	376
10	Early	Frequent	Short	60	29	379
11	Early	Infrequent	Long	55	31	411
12	Early	Very Infrequent	Very Long	53	34	425

Although managers may prefer less frequent interruptions, the findings show that frequent, short rework cycles produce smaller queues and faster recovery. Across all 12 DES scenarios, this rework pattern consistently generated the highest number of completed buildings, the lowest work-in-progress, and the shortest project duration, regardless of whether the call-back occurred early, on time, or late. These results are consistent with and support the computational modeling outcomes.

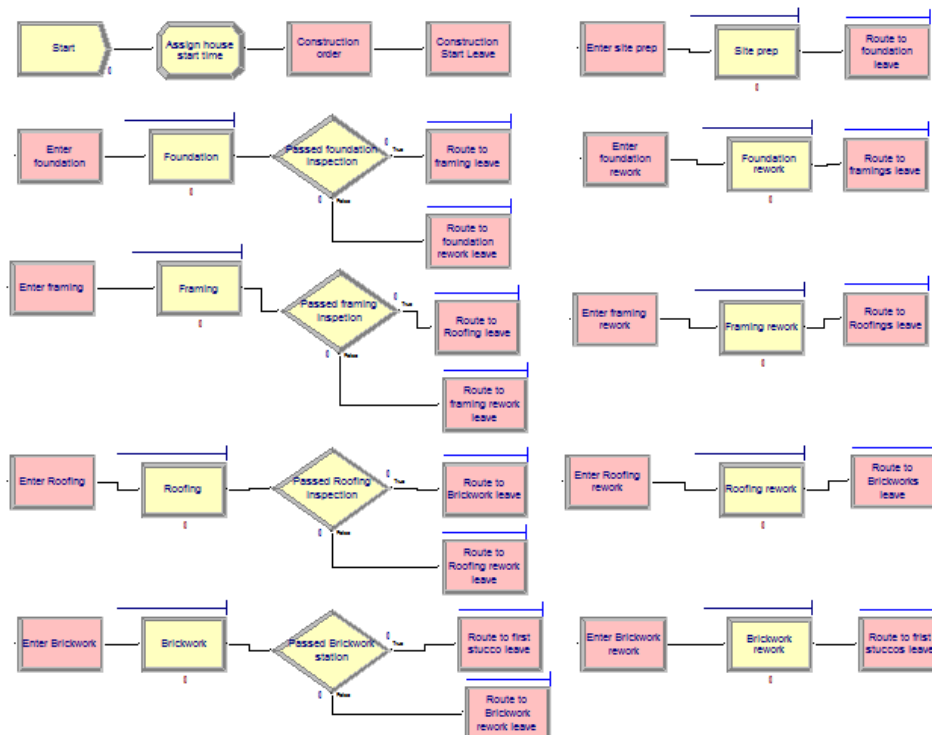


Figure 3. The simulation model developed in ARENA 14 software

4.2 Application of the Proposed Method in a Real-World Case Study

To demonstrate practical applicability, the proposed two-phase simulation-optimization framework was implemented on a construction case study to minimize rework expenditures per shift. In the initial phase, Arena's built-in optimizer, OptQuest®, was utilized to search for optimal operational parameters driven by simulation outputs. OptQuest® integrates multiple metaheuristic mechanisms:

- **Scatter Search:** Acts as the primary exploration engine, generating reference vectors and diverse solution sets.
- **Tabu Search:** Uses adaptive memory structures to avoid revisiting previously evaluated candidate solutions.
- **Artificial Neural Networks:** Serves as a predictive surrogate to estimate objective function performance and filter non-dominated trade-offs.

Configuring OptQuest® required establishing the objective function and decision variables to curtail rework costs via accelerated project delivery. The search domain was constrained by defining upper and lower parameter bounds within the setup environment (Table 6), while the mathematical formulation of the cost-minimization model is specified in Equation (3).

Table 6. Pre-determined Parameters for OptQuest® Settings

Parameters	Lower Bound (LB)	Upper Bound (UB)	Unit
Workforce Experience	1 (Very Low)	7 (Very High)	-
Conflict among Stakeholders	1 (Very Low)	7 (Very High)	-
Political Status	1 (Very Low)	7 (Very High)	-
Payment Delays	30	180	Days

(3)

$$MaxTP = E(f_0(x))$$

s. t

$$L_s \leq S_{labour} \leq U_s$$

$$L_l \leq L_{participant} \leq U_l$$

$$L_o \leq O_{politic} \leq U_o$$

$$L_w \leq W_{payment} \leq U_w$$

$$S_{out}, O_{out}, L_{out}, W_{out} \geq 0$$

By applying the specified settings and defining the problem, the model is constructed in OptQuest®. The best simulation value is obtained at iteration 85 out of the 25 combinations defined in the equation set. In this iteration, the total cost is calculated as 57.799 million Rials. Under this scenario, the reported values are 3.043 (low) for workforce experience, 1.5336 (very low) for conflict among stakeholders, 3.1254 (low) for political status, and 1.196 (very low) for payment delays. Table 7 presents a comparison between the optimal and current states of the building construction process. According to the obtained optimal combination, the optimal state is more balanced compared to the current state. Based on the results achieved by implementing this combination, the cost output has been reduced from 57.799 to 47.403 (million Rials). Finally, the first phase of the proposed method concludes by selecting an acceptable feasible combination.

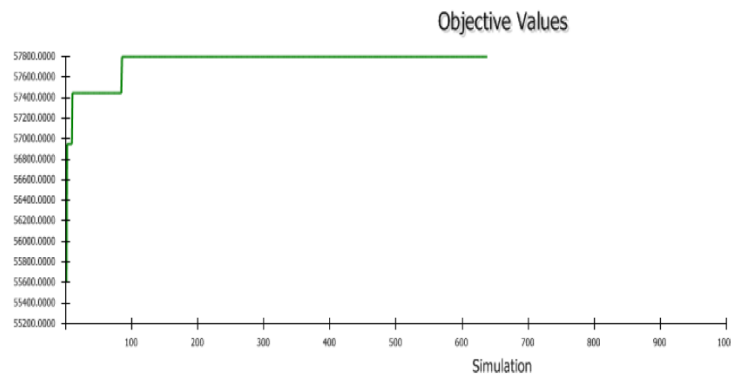


Figure 4. Total system cost per simulation iteration

Table 7. Comparison of Current and Optimal Construction States

Status	Decision variables				Total Cost (Million Rials)
	$W_{payment}$	$O_{politic}$	$L_{payment}$	S_{labour}	
Current	9.019	1.5121	6.094	1.7422	57.799
Optimum	1.196	3.1254	1.5336	3.043	47.403

4-3 Modeling to Determine the Magnitude of Factors Affecting Construction Rework

The second phase involved running the validated simulation model to assess system performance across various scenarios. The model, developed in Arena, accurately represents the building construction process, with results showing no statistically significant differences at the 95% confidence level across all tested configurations. For simulation execution, each replication was set to one month (24 working days), and 10 replications were deemed sufficient based on half-width confidence interval analysis of key performance metrics. A four-day warm-up period was incorporated to ensure the system reached a stable, steady-state condition before data collection. Statistical distributions for core research variables, selected for their goodness-of-fit using the Arena Input Analyzer, were integrated into the model. The simulations were run on a standard personal computer.

Table 8. Comparison of Current and Optimal Construction States

Variable Type	Combination (Low, Current, High)
Labor experience	(1,3,7)
Conflict among participants	(1,5,7)
Political situation	(1,3,7)
Payment delays	(25,36,45)

Based on the previous discussion, project managers seek to identify the optimal combination of key variables according to their constraints in order to:

1. maximize the number of completed units,
2. minimize the total cost, and
3. minimize the delay time.

The optimization problem is mathematically formulated as follows:

$$\begin{aligned}
 &(4) \\
 &\max f_1(X_1, X_2, X_3, X_4) \\
 &\min f_2(X_1, X_2, X_3, X_4) \\
 &\min f_3(X_1, X_2, X_3, X_4) \\
 &s. t. \\
 &L_i \leq x_i \leq U_i \quad \text{for } i = 1, 2, 3, 4 \\
 &x_i \text{ integer}
 \end{aligned}$$

This is an integer multi-objective optimization problem. The functions in this problem do not have an analytical form and must be evaluated through simulation in accordance with the framework presented in this dissertation. L_i and U_i represent the minimum and maximum levels of the variables in the set, respectively. The first step in developing the surrogate model within the design-of-experiments (DoE) stage is to select the input variables and their considered levels under the system constraints. These variables and their levels are as follows:

- X_1 : Labor experience (A), with a minimum value of 1 and a maximum value of 7;
- X_2 : Conflict among participants (B), with a minimum value of 1 and a maximum value of 7;
- X_3 : Political situation (C), with a minimum value of 1 and a maximum value of 7;
- X_4 : Payment delay (D), with a minimum value of 25 and a maximum value of 45.

Four independent input factors (A, B, C, and D) with 7, 7, 7, and 7 respective levels govern the three simulation responses: maximizing completed units, minimizing total cost, and minimizing project delays. Rather than running a computationally prohibitive full factorial search ($7 \times 7 \times 7 \times 7 = 2401$ runs per objective, totaling 7203 evaluations), a regression-based surrogate modeling strategy was implemented.

A 25-run Central Composite Design (CCD) was adopted to sample the input domain. Each experimental point was evaluated over 10 simulation replications, using mean response values for metamodel fitting. Candidate polynomial approximations for each performance measure were appraised via goodness-of-fit metrics:

- **Coefficient of Determination (R^2):** Measures the proportion of response variance captured by the model, where higher values indicate close alignment between simulated outputs and metamodel predictions.
- **Prediction Error Sum of Squares (PRESS):** Gauges out-of-sample generalizability, with lower scores indicating superior predictive capability on unseen operating points.
- **p-value:** Evaluates the statistical significance of the fitted terms.

The comparative statistical performance and model selection metrics across all three objectives are detailed in Tables 9, 10, and 11.

Table 9. Model accuracy for maximizing the number of completed units using two regression functions

Source	P-Value	PRESS	R^2
Proposed Model	0.0000	7898	0.8232
Two Factor Interactions Model	0.4636	9620	0.4242

Table 10. Model accuracy for the cost function

Source	P-Value	PRESS	R^2
Proposed Model	0.0000	0.01	0.9897
Linear Model	0.0000	0.4	0.8896

Table 11. Model accuracy for the delay time function

Source	P-Value	PRESS	R ²
Proposed Model	0.0000	856	0.8602
Linear Model	0.6244	1065	0.6870
Two Factor Interactions Model	0.2136	2365	0.5036

The accuracy analysis reported in Tables 9–11 confirms that the modified surrogate model provides reliable predictions for all three objectives. Accordingly, the significant model effects and their coefficients were estimated for completed units, total cost, and delay duration, as summarized in Tables 12–14. The close correspondence between observed simulation outputs and model predictions supports the adequacy of the fitted models. Terms with Prob - F < 0.05 or an absolute t-value greater than 1.96 were regarded as statistically significant.

Table 12. Estimated coefficients and model effects for completed units

Source	Coef	S.E Coef	P-Value	t-value
Intercept	15106.03	3.14	0.0260	4810.8375
X_1	-0.40	1.84	0.8316	-0.2173
X_2	12.50	3.19	0.0020	3.9184
X_3	3.10	1.84	0.1180	1.6847
X_4	-2.18	1.84	0.2585	-1.1847
X_1X_2	-3.00	2.25	0.2080	-1.3333
X_1X_3	-4.93	2.25	0.0495	-2.1911
X_1X_4	-1.18	2.25	0.6117	-0.5244
X_2X_4	-1.00	2.25	0.6652	-0.4444
X_1^2	2.25	1.88	0.2545	1.1968
X_2^2	-3.07	1.88	0.1283	-1.6329
$X_1X_2X_4$	5.75	2.25	0.0254	2.5555
$X_1^2X_2$	-13.10	3.90	0.0057	-3.3589

Table 13. Estimated coefficients and model effects for cost

Source	Coef	S.E Coef	P-Value	t-value
Intercept	98.68	0.87	0.0053	113.4252
X_1	-1.93	0.88	0.0511	-2.1931
X_2	1.09	0.88	0.2432	1.2386
X_3	0.58	0.88	0.5260	0.6591
X_4	0.013	0.88	0.9889	0.0147
X_1X_2	0.47	1.08	0.6721	0.4351
X_1X_3	1.26	1.08	0.2685	1.1666
X_1X_4	-0.69	1.08	0.5367	-0.6388
X_2X_3	2.88	1.08	0.0219	2.66
X_2X_4	-3.01	1.08	0.0177	-2.7875
X_3X_4	-3.07	1.08	0.0162	-2.8426
$X_1X_2X_3$	-2.69	1.08	0.0303	-2.4907
$X_1X_2X_4$	4.25	1.08	0.0024	3.9351
$X_1X_3X_4$	3.91	1.08	0.0041	3.6204

Table 14. Estimated coefficients and model effects for delay time

Source	Coef	S.E Coef	P-Value	t-value
Intercept	60.32	1.08	0.0001	-2.9426
X_1	2.29	1.08	0.0001	-2.9426
X_2	0.98	1.08	0.0001	-2.9426
X_3	0.91	1.08	0.0001	-2.9426
X_4	1.87	1.08	0.0001	-2.9426
X_1X_2	-0.038	1.08	0.0001	-2.9426
X_1X_3	-0.035	1.08	0.0001	-2.9426
X_1X_4	-0.071	1.08	0.0001	-2.9426
X_2X_3	-0.015	1.08	0.0001	-2.9426
X_2X_4	-0.031	1.08	0.0001	-2.9426
X_3X_4	-0.029	1.08	0.0001	-2.9426
X_1^2	-0.044	1.08	0.0001	-2.9426
X_2^2	-0.008	1.08	0.0067	-2.9426
X_3^2	-0.007	1.08	0.0142	-2.9426
X_4^2	-0.029	1.08	0.0001	-2.9426

Based on the statistical analyses conducted, the surrogate models for completed units, cost, and delay time are formulated as follows:

$$Y_1 = 15106.03 - 0.4X_1 + 12.5X_2 + 3.10X_3 - 2.18X_4 - 4.93X_1X_3 + 5.75X_1X_2X_4 - 13.10X_1^2X_2 \quad (5)$$

$$Sqrt(Y_3) = 98.68 - 1.93X_1 + 1.09X_2 + 0.58X_3 + 0.013X_4 + 2.88X_2X_3 - 3.01X_2X_4 - 3.07X_3X_4 - 2.69X_1X_2X_3 + 4.25X_1X_2X_4 + 3.91X_1X_3X_4 \quad (6)$$

$$\text{Sqrt}(Y_2) = 60.32 + 2.29X_1 + 0.98X_2 + 0.91X_3 + 1.87X_4 - 0.038X_1X_2 - 0.035X_1X_3 - 0.071X_1X_4 - 0.051X_2X_3 - 0.031X_2X_4 - 0.029X_3X_4 - 0.044X_1^2 - 0.008X_2^2 - 0.007X_3^2 - 0.029X_4^2 \quad (7)$$

Project managers can utilize the aforementioned surrogate models once the validation of all functions is approved. Simulation validation measures how well the model represents the requirements of the real-world system. To validate the surrogate models developed in this thesis, the most common error estimation method, denoted as $RMSE_{PRESS}$ and calculated using the formula $\sqrt{\frac{PRESS}{n}}$, has been employed.

Table 15. Validation results

Objective function	$RMSE_{PRESS}$
(Y_1)	$RMSE_{PRESS}^{Modified} = 17.94$
	$RMSE_{PRESS}^{2FI} = 18.44$
(Y_2)	$RMSE_{PRESS}^{Modified} = 0.048$
	$RMSE_{PRESS}^{Linear} = 0.1$
(Y_3)	$RMSE_{PRESS}^{Modified} = 7.83$
	$RMSE_{PRESS}^{Linear} = 9.15$
	$RMSE_{PRESS}^{2FI} = 13.14$

Table 15 compares the $RMSE_{PRESS}$ values of the modified and alternative models for each objective. The results indicate that the modified models achieve satisfactory predictive performance and can therefore serve as reliable surrogate representations of the simulation model.

4.4 Modeling to Determine the Magnitude of Factors Affecting Construction Rework

Based on the estimated models for the three response levels considered, the mathematical programming problem is formulated according to the following set of equations (8):

(8)

Maximize $(Y_1(x))$

Minimize $(Y_2(x))$

Minimize $(Y_3(x))$

s. t.

$1 \leq x_1 \leq 7$

$1 \leq x_2 \leq 7$

$1 \leq x_3 \leq 7$

$25 \leq x_4 \leq 45$

x_i integer for $i = 1, 2, 3, 4$

In the considered multi-objective integer nonlinear programming (MOINLP) problem, Y_1 represents the function for completed units, Y_2 denotes the total cost function, and Y_3 is the delay function (as specified in the model equations). Here, xxx is the vector of design variables, which includes labor experience, conflict between participants, political status, and payment delays. All three functions were derived using the previously described analyses. The multi-objective problem was solved in LINGO 18 using the Modified Normal Boundary Intersection (NBI) method and three surrogate models. The analysis used four significant digits and six initial points, while Maple 2021 was applied to assess solution quality. The three objectives were normalized to the $[0,1]$ interval and visualized through three-dimensional Pareto-frontier plots. The optimization initially produced 43 non-dominated solutions, from which 19 high-quality solutions were retained to form the final Pareto set. These solutions represent the trade-offs among the three conflicting objectives. Comparison with the current-state configuration showed that the proposed surrogate-based optimization framework generated substantially better alternatives. Accordingly, engineers can select suitable decision-variable values from the final Pareto frontier based on their preferred balance among project completion, cost, and delay objectives.

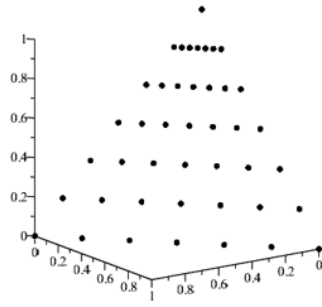


Figure 5. Three-dimensional plot of the normalized objective-function points

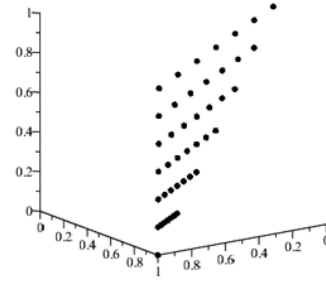


Figure 6. Overall points of the generated Pareto set

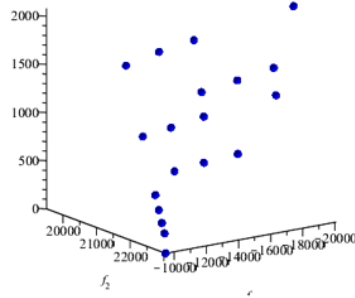


Figure 7. Values of the objective functions

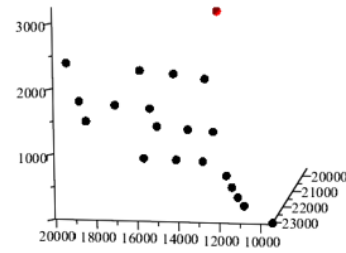


Figure 8. Comparison of the current state and the developed model

4.4.1 Comparative Performance Analysis

To evaluate the efficiency of the proposed Modified NBI approach, we performed a comparative analysis against the Standard NBI method and the NSGA-II metaheuristic. The performance was assessed based on computational time (CPU time) and the quality of the Pareto frontier (Spacing and Hypervolume metrics). As shown in Table 16, the Modified NBI outperformed both benchmarks.

Algorithm	CPU Time (s)	Spacing (S)	Hypervolume (HV)
Standard NBI	68.3	0.089	0.781
NSGA-II	184.2	0.076	0.805
Modified NBI	42.6	0.041	0.842

The Modified NBI exhibited the lowest computational overhead (42.6s), attributed to its adaptive iteration control which mitigates the redundant subproblem resolution common in standard NBI. Furthermore, the lower Spacing value (0.041) and higher Hypervolume (0.842) confirm that the modified algorithm successfully produced a more uniform and diverse distribution of non-dominated solutions compared to both the classic NBI and metaheuristic approaches.

5. Conclusion

This study was conducted with the aim of identifying and controlling the factors influencing rework in residential buildings, presenting a surrogate-model-driven multi-objective optimization framework to improve decision-making in construction management. The research data were gathered from a real residential project in Tehran, as well as a dataset of construction projects across the Middle East. Subsequently, by employing Central Composite Design (CCD) and statistical model evaluation criteria, a suitable surrogate model was selected to predict the objective functions. The results demonstrated that the modified model exhibits acceptable accuracy in estimating key performance indicators, establishing a good agreement between the observed and predicted values. In the optimization phase, the implementation of the Modified NBI algorithm led to the extraction of a set of non-dominated solutions and the formation of a Pareto frontier. This enables the visualization and management of the trade-offs between increasing the number of completed units, reducing costs, and minimizing delay times. The analysis of the resulting solutions indicated that the proposed framework offers superior decision-making options compared to the current state (status quo) and can serve as a basis for selecting executive and design policies to enhance project performance. Overall, the findings confirm that combining the identification of rework-influencing factors

with surrogate modeling and multi-objective optimization can be utilized as a practical approach to mitigate the consequences of rework and enhance the efficiency of residential projects. This is particularly significant as the Pareto frontier allows managers and engineers to make transparent and well-documented decisions tailored to project priorities (cost, time, and completed units output). Future research can extend and strengthen the present work by generalizing the proposed framework to other types of construction projects and different geographic contexts, while also employing advanced machine learning algorithms and deep neural networks to improve the predictive accuracy of surrogate models. In addition, incorporating quality, safety, and environmental sustainability indicators into the objective functions, and ultimately integrating this approach with technologies such as Building Information Modeling (BIM) and digital twins for real-time monitoring and intelligent prevention of rework, can pave the way toward more automated and effective construction management systems.

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