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# Optimization-Oriented Final Construction Cost Forecasting under Price Uncertainty: An Integrated Building Information Modeling and Adaptive Neuro-Fuzzy Inference Framework

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**Abstract.** Accurate forecasting of final construction costs is important for project planning and cost control in inflation-sensitive construction markets. This study develops a BIM-integrated artificial neural network (ANN) workflow that links item-level Fehrestbaha data and official construction adjustment indices to BIM components and forecasts unit costs at a user-specified completion date. Historical cost information for sixteen materials over 2013–2022 was used to develop the deterministic ANN predictor, and the resulting unit-cost forecasts were returned to the BIM quantity-takeoff workflow. The framework was evaluated on a single nine-story residential building in Tehran by comparing the April 2022 initial estimate, the ANN-based December 2023 forecast, and the actual final project cost. The December 2023 case lies beyond the 2013–2022 historical development horizon and is therefore used as the principal project-level temporal check, whereas the internal training/test diagnostics are interpreted only as model-fit diagnostics because the monthly resampling procedure can induce dependence among adjacent observations. For this case, the absolute project-level deviation was 11.30% for the ANN forecast compared with 23.89% for the initial no-update estimate. The contribution is the automated linkage of national item coding, time-indexed cost information, ANN forecasting, Revit plug-ins, and BIM quantity aggregation rather than a new optimization algorithm or a probabilistic uncertainty model. The results support the feasibility of the workflow as a proof of concept, subject to stricter chronological validation, improved categorical encoding, benchmark comparisons, and multi-project external validation.

**Keywords.** Building Information Modeling (BIM), Artificial Neural Network (ANN), Construction cost forecasting, Fehrestbaha, National adjustment indices, Quantity takeoff.

**MSC.** 68T07; 90B50; 62P30.

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## 1 Introduction

Civil projects significantly impact quality of life, economic stability, and social development [30]. In developing countries, effective project management depends on timely delivery, budget compliance, and specification adherence [2]. The construction industry is frequently criticized for cost overruns and delays, with project cost performance remaining a central management concern [10]. Accurate early-stage cost forecasting is essential for improving feasibility under uncertainty due to limited technical information [7, 25]. While perceived and actual costs differ until project completion, profitability depends on alignment between estimated and final costs [41, 46]. Cost knowledge remains critical for stakeholders [26]. However, cost estimation is challenged by overruns, delays, scope changes, contingencies, and inflation [38]. These issues are more severe in developing countries, where infrastructure projects frequently suffer from delays and budget overruns [4]. This is particularly evident in inflation-sensitive economies such as Iran [11]. In such contexts, cost increases are driven by inflation neglect, poor budgeting, resource misallocation, cash flow issues, material price volatility, miscommunication, WBS deficiencies, and exchange rate fluctuations [21, 22, 48, 50].

The accuracy of cost estimates is a primary concern for project stakeholders, as inaccuracies can significantly affect project performance and objective achievement [17]. In construction, reliable cost prediction is essential for managing budget risks, since both overestimation and underestimation may lead to financial losses. However, estimation is often complicated by numerous cost drivers, time limitations, and incomplete information. Design changes during project execution further increase the need for accurate forecasting methods. Traditionally, manual calculations were used, but they are insufficient due to the complex interaction of variables. Although tools such as Excel, Access, and SPSS are widely used, they are limited in handling this complexity. As a result, researchers have increasingly focused on advanced statistical models and machine learning (ML) techniques to improve accuracy and reduce estimation errors [20, 29, 36, 52, 53]. Emerging technologies such as artificial intelligence (AI) and ML are considered promising solutions for improving cost estimation and supporting decision-making [23]. ML improves performance by learning from historical data, identifying patterns, and extracting insights while reducing redundancy [5, 16, 62].

Cost estimation systems commonly use AI techniques such as regression models and artificial neural networks (ANNs) [28, 31, 51]. ANNs replicate aspects of biological neural networks and are capable of learning and pattern recognition, making them suitable for complex problems [34]. However, ANNs suffer from limitations, particularly their black-box nature, which reduces interpretability. In addition, ML models require high-quality data, and insufficient datasets can reduce prediction reliability. Despite these limitations, ANN-based models have demonstrated high predictive accuracy, in some cases reaching up to 98% [6, 9, 14, 27, 32, 35, 54, 55, 58]. Quantity take-off and cost estimation are labor-intensive and prone to errors. Inaccuracies in quantity take-off can directly lead to cost estimation errors [13]. Automating data collection improves accuracy and reduces errors [40]. The construction industry increasingly relies on digital tools, with BIM as a key innovation [43]. Recent comparative work has benchmarked ANN against natural gradient boosting (NGBoost) and linear regression with SHAP-based interpretation [18], while recent hybrid estimate-at-completion research has combined ANN/ANFIS with metaheuristic optimization [3].

BIM improves coordination and information flow, and aligns architectural and structural designs while supporting project execution [56]. The effectiveness of BIM implementation depends on clearly defined performance metrics that allow organizations to systematically evaluate their capabilities and improve decision-making processes throughout project delivery [49]. These tools also enhance visualization, improving communication and collaboration among stakeholders [8]. BIM-based quantity take-off provides a faster and more reliable alternative to traditional methods [39]. Integration of cost data into BIM (5D BIM) can reduce costs and delays [45]. Additionally, BIM-enabled digital technologies contribute to sustainability in construction projects [15].

Despite its advantages, BIM adoption for cost estimation remains limited mainly due to insufficient alignment with relevant standards [44]. Many BIM tools are not fully compatible with measurement standards, particularly in developing countries [1]. Building on these limitations, studies in developing contexts indicate that BIM implementation is further constrained by institutional and organizational barriers that hinder effective adoption [24].

As a result, researchers are exploring standardized frameworks for integrating BIM with cost estimation [42]. Additionally, the final settlement price often deviates from the initial contract price due to various factors. These adjustments are largely influenced by human-related elements, which remain an area where BIM has limited capability for effective management [59]. A recent systematic review of 77 studies further shows that AI/ML–BIM integration spans component classification, quantity take-off, and final cost estimation [37]. Previous studies can be categorized into several areas, including BIM, cost estimation, machine learning, economic and inflation-related factors, cost standards, and adjusted final project cost computation. Table 1 compares the current study with these prior works.

Banihashemi et al. [11] demonstrated machine-learning integration with 5D BIM and an Iranian cost-estimation classification prototype, while Dastgheib et al. [19] evaluated ANFIS for estimate-at-completion forecasting in an earned-value and risk-based setting. More recent BIM-linked neural cost models have combined BIM with a PSO-enhanced Elman neural network [60] and BIM5D with an SSA-optimized PGNN [33], reinforcing the broader trend toward integrated digital cost-prediction workflows. The present study therefore does not claim algorithmic novelty from ANN/ANFIS forecasting itself. Its contribution is narrower and operational: historical Fehrestbaha item prices and official adjustment indices are linked to material identifiers, forecast for a user-specified completion date, and returned through Revit plug-ins to

**Table 1:** Comparative review of related research

| Authors/Year | Focus Area: BIM | Cost Estimation | Machine Learning | Economic/ inflation factors | Application of cost standards | Computation of adjusted final project cost |
|---|---|---|---|---|---|---|
| Khosakitchalert, Yabuki and Fukuda [39] | ✓ | ✓ | | | | |
| Banihashemi et al. [11] | ✓ | ✓ | ✓ | | ✓ | |
| Alqahtani and Whyte [6] | | ✓ | ✓ | | | |
| Zhao, Mbachu and Liu [61] | | ✓ | ✓ | ✓ | | |
| Wang et al. [57] | | ✓ | ✓ | ✓ | | |
| Tayefeh Hashemi, Ebadati and Kaur [53] | | ✓ | ✓ | | | |
| Egwim et al. [23] | | | | ✓ | | |
| Okpala and Aniekwu [47] | | | | ✓ | | |
| Baloi and Price [10] | | | | ✓ | | |
| Bayram and Al-Jibouri [12] | | ✓ | ✓ | ✓ | | |
| **This study (2026)** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

the BIM quantity-takeoff workflow for project-level cost computation. Relative to stand-alone or generic cost datasets, this linkage preserves the statutory item coding, measurement units, and adjustment structure used in Iranian project estimation. Accordingly, novelty is claimed at the systems-integration level rather than at the forecasting-algorithm level.

Prior research has established the value of machine learning for construction cost estimation, but two gaps remain relevant to the present application. First, many models target early-stage estimates rather than updating item-level costs at a user-defined completion date. Second, economic indices and statutory item coding are often processed outside the BIM authoring and quantity-takeoff workflow. The present study therefore focuses on operational integration rather than algorithmic novelty. It couples historical Fehrestbaha item prices and official adjustment indices with Revit-linked material codes, uses ANN forecasting to obtain completion-date unit prices, and returns those prices to BIM quantity takeoff for project-level cost computation. This arrangement also allows the cost effect of a revised completion date or design change to be examined within a common cost-information workflow. This comparison with Banihashemi et al. [11] and Dastgheib et al. [19] frames the research gap as an end-to-end BIM–Fehrestbaha forecasting integration rather than as the introduction of a new ANN/ANFIS method.

On this basis, the study objective is to implement and evaluate an ANN-assisted BIM workflow that forecasts completion-date unit costs from historical Fehrestbaha prices and official adjustment-index data and propagates those forecasts through BIM-derived quantities. The study evaluates a deterministic forecasting workflow; it does not formulate a project optimization problem and does not quantify forecast uncertainty probabilistically. The empirical question is whether, for the selected project, the completion-date ANN estimate is closer to the actual final cost than the initial no-update Fehrestbaha estimate.

The remainder of this paper is organized as follows. Section 2 presents the research methodology, describing the five implementation phases: development of the 3D BIM model, construction of the Fehrestbaha–BIM cost database, linkage of Fehrestbaha items to BIM elements, preparation of the historical cost dataset and training of the ANN forecasting module, and generation of completion-date cost forecasts. Section 3 reports the results obtained from the case-study building, including the material-level price escalation, the comparison of actual, initial, and ANN-forecast project costs, and the associated error metrics. Section 4 discusses these findings together with the scope boundaries and limitations of the proposed workflow. Finally, Section 5 concludes the paper and outlines directions for future validation.

## 2 Research Methodology

Early prediction of cost escalations is crucial for managing project cash flow and remains important throughout the project lifecycle for evaluating the impact of design changes. In this study, "design changes" refers to modifications in plans, materials, and execution details. With increasing BIM adoption in countries such as Iran, integrating cost escalation prediction into BIM is essential. The methodology follows Figure 1 to develop and implement cost prediction capabilities in BIM.

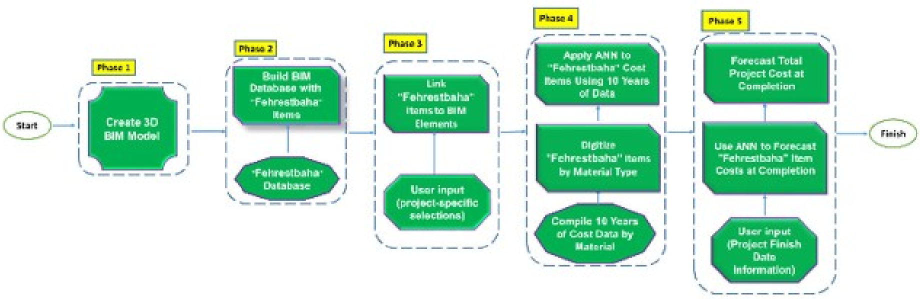



**Figure 1:** Research processes utilized

### 2.1 Phase 1: Developing the 3D BIM Model

A 3D BIM model was developed as the structured geometric and quantity platform for the cost-forecasting workflow. It includes key building elements such as walls, floors, ceilings, doors, and windows and links those elements to historical Fehrestbaha cost information used by the ANN forecasting module.

### 2.2 Phase 2: Establishing the Fehrestbaha–BIM Cost Database

Phase 2 creates the item-level cost-information layer required by the forecasting workflow. Official Fehrestbaha records are structured and imported into BIM so that each model object can be associated with a standardized item code, unit, and base price.

#### 2.2.1 Database of Fehrestbaha

In Iran, civil project pricing is based on annual rates issued by the Plan and Budget Organization, determined annually under Article 23 of the Budget Law, and consists of multiple branches. These price lists form the basis of initial estimates under Article 80 of the General Accounting Law. Fehrestbaha defines unit prices (Rials per unit volume or service) and is updated annually. This study uses the 2022 Building and Industrial Building Fehrestbaha price list. Each item has a six-digit code representing its classification: the first two digits indicate the chapter, the next two the material type, and the last two the material detail. For example, item 080101 represents concrete, including specifications such as "concrete made of washed natural or crushed sand" and "concrete with 100 kg of cement per cubic meter" (Figure 2).

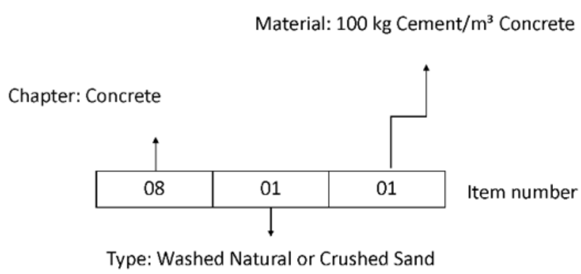



**Figure 2:** Dividing the digits of the Fehrestbaha item

#### 2.2.2 Developing BIM Database Using Cost Items in Fehrestbaha

A BIM material database was created using Fehrestbaha cost items. All items were compiled in Excel and structured into columns (chapter, item number, description, unit, unit price). A BIM plug-in was developed to import this data into the BIM environment (Figure 3).

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | Chapter number | Item number | Description | Unit | Unit price (riyal) | Unit2 |
| 596 | 13 | 130101 | Waterproofing, with a layer of bituminous coating. | SM | 280,500 | SM |
| 597 | 13 | 130102 | Moisture insulation, using emulsion bitumen. | SM | 163,000 | SM |
| 598 | 13 | 130108 | Moisture insulation, using soluble bitumen. | SM | 208,500 | SM |
| 599 | 13 | 130109 | Surcharge to rows 130102 and 130108 in case of modification of bitumen with polymer materials. | SM | 18,600 | SM |

**Figure 3:** An example of Fehrestbaha items in Excel

## 2.3 Phase 3: Linking Fehrestbaha Items to BIM Elements

BIM elements such as walls, floors, ceilings, roofs, doors, and windows were linked to Fehrestbaha items. For example, a wall consists of multiple cost items (plaster, brick, tiles), each linked to corresponding Fehrestbaha entries (Figure 4). This process was repeated for all components.

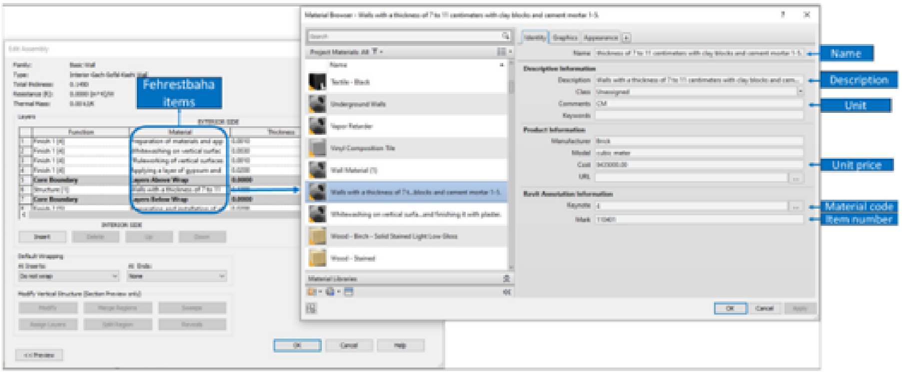



**Figure 4:** Linking Fehrestbaha items to elements in BIM



## 2.4 Phase 4: Preparing Historical Cost Data and Training the ANN

Phase 4 constructs the time-indexed material-cost dataset, assigns material codes, and trains the ANN that supplies forecast unit prices to the BIM model.

### 2.4.1 Developing Historical Cost Data for Sixteen Materials

Historical Fehrestbaha data for sixteen commonly used materials were compiled for 2013–2022 together with official quarterly construction adjustment indices issued by the Plan and Budget

Organization. The adjustment index represents time-varying construction-sector price conditions and was used to align item-price variation with the forecasting horizon.

The official adjustment-index record spans 2013–2022 and contains 40 quarterly observations over the ten-year period. For monthly alignment with the ANN date inputs, values between consecutive quarterly anchors were obtained by linear interpolation, yielding a 120-month computational series. The 80 interpolation-derived monthly positions are temporally derived from the quarterly series and are therefore treated as resampled values rather than independent market observations. Accordingly, Figure 10 is interpreted as an internal model-fit diagnostic, while the December 2023 project case provides the post-development temporal assessment. For confirmatory time-series validation, a strict chronological or rolling-origin design at the native quarterly level is recommended.

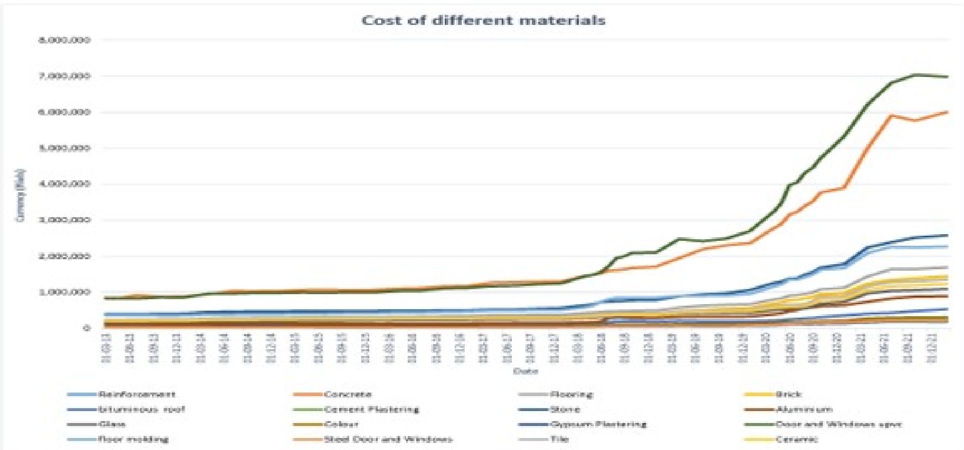
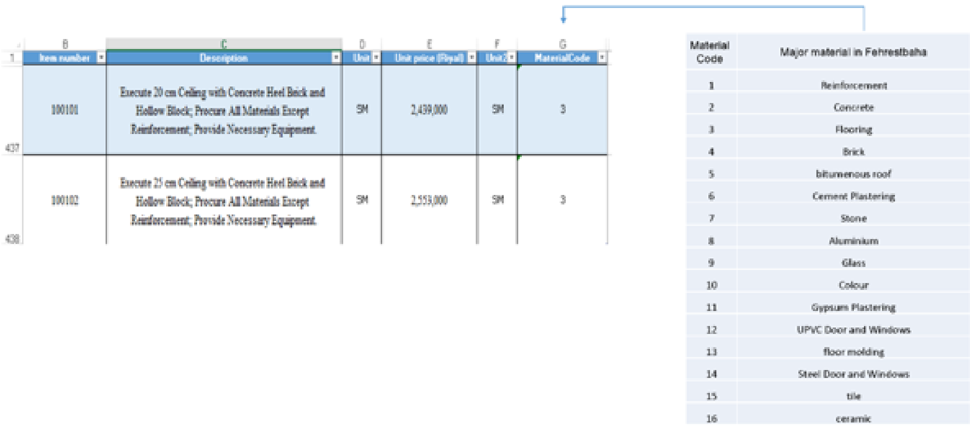



**Figure 5:** Cost data for sixteen commonly used materials over a 10-year period

### 2.4.2 Digitization of Fehrestbaha Items by Material Type

The forecasting dataset uses cost information for sixteen major materials over the historical period. Material information was digitized, transformed into a machine-readable format, and linked to the corresponding Fehrestbaha items. The sixteen materials are represented by integer identifiers (1–16) together with year and month. These identifiers function as categorical administrative labels rather than quantitative material attributes; their purpose is to distinguish material classes within the integrated BIM–ANN workflow. Because integer labels can introduce an ordinal structure into model inputs, this representation is treated as a modelling simplification rather than a physical scale. Future encoding-sensitivity analyses can compare one-hot encoding, learned embeddings, physically meaningful attributes, or material-specific models.

Within Revit, the material code is written to the Keynote parameter and provides the link between each element's Fehrestbaha mapping and the ANN input record shown in Figure 6.



| Item number | Description | Unit | Unit price (Riyal) | Unit2 | MaterialCode |
|---|---|---|---|---|---|
| 100101 | Execute 20 cm Ceiling with Concrete Heel Brick and Hollow Block; Procure All Materials Except Reinforcement; Provide Necessary Equipment | SM | 2,439,000 | SM | 3 |
| 100102 | Execute 25 cm Ceiling with Concrete Heel Brick and Hollow Block; Procure All Materials Except Reinforcement; Provide Necessary Equipment | SM | 2,553,000 | SM | 3 |

| Material Code | Major material in Fehrestbaha |
|---|---|
| 1 | Reinforcement |
| 2 | Concrete |
| 3 | Flooring |
| 4 | Brick |
| 5 | bitumenous roof |
| 6 | Cement Plastering |
| 7 | Stone |
| 8 | Aluminium |
| 9 | Glass |
| 10 | Colour |
| 11 | Gypsum Plastering |
| 12 | UPVC Door and Windows |
| 13 | floor molding |
| 14 | Steel Door and Windows |
| 15 | tile |
| 16 | ceramic |

**Figure 6:** Digitization of Fehrestbaha items by material type utilized

### 2.4.3 Training and Evaluating the ANN on Historical Cost Data

The implemented forecasting model was an artificial neural network (ANN), not ANFIS. It was trained on the 2013–2022 time-indexed cost records for sixteen materials. Data were prepared in Excel, transferred to MATLAB through the Revit-linked workflow, and forecast unit costs were returned to BIM. The input vector for material $m$ at time $t$ is

$$x(m,t) = \big[\, Y(t),\ M(t),\ c(m) \,\big]^T, \tag{1}$$

where $Y(t)$ is calendar year, $M(t)$ is month, and $c(m)$ is the material identifier; the target $y(m,t)$ is the corresponding unit cost. The same three-variable input definition is used throughout Sections 2.4.3 and 2.5. All numerical predictions reported in Tables 2–4 and Figures 10, 14, and 15 were generated by this ANN; ANFIS is not part of the implemented computational pipeline.

**ANN implementation steps in the BIM environment.**

**Step 1. Transfer cost data for sixteen materials from Excel to the Revit environment.** Cost data for sixteen materials were encoded in Excel and linked to relevant Fehrestbaha items, then transferred to Revit through a developed add-on.

**Step 2. Transfer 10 years of input and output data for ANN training to MATLAB.** The collected data were organized and normalized in Excel and transferred to MATLAB. Inputs

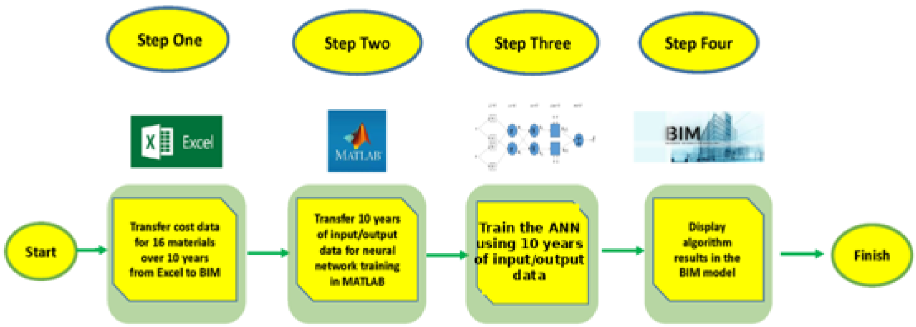



**Figure 7:** Workflow of ANN implementation in the BIM model

included year, month, and material code, while outputs were the corresponding cost data for each year–month–material combination. Figure 8 displays these inputs and outputs, which correspond to the pre-normalized data, providing a clearer presentation of the model inputs and outputs.

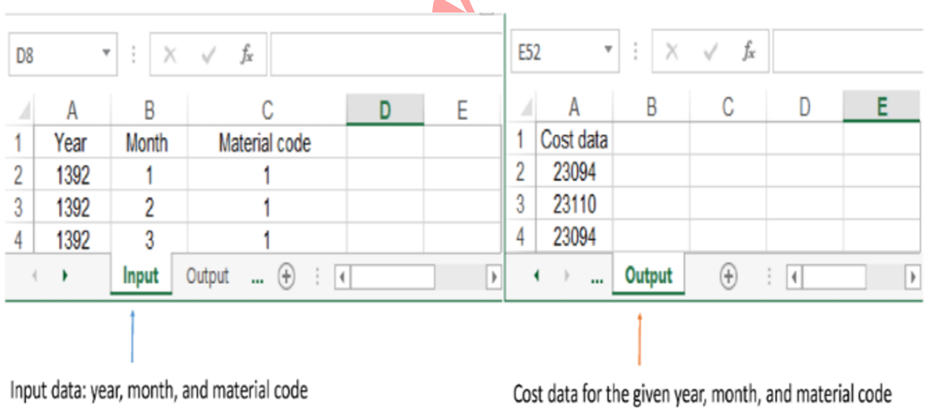



**Figure 8:** Inputs and outputs used for ANN training

**Step 3. Train and evaluate the ANN using 10 years of input and output data.** The normalized dataset was used to fit the ANN in MATLAB. For $N$ training records, $\theta^*$ is obtained by minimizing

$$\theta^* = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \left[y_i - f_\theta(x_i)\right]^2, \tag{2}$$

consistent with the mean-squared-error (MSE) training history reported in Figure 10. This loss minimization is ordinary model fitting and is not the project-level optimization formulation that would be required to justify an "optimization-oriented" contribution. The ANN returns a deterministic point estimate of unit cost; no prediction interval, probability distribution, Monte

Carlo propagation, quantile forecast, or other quantitative uncertainty measure is produced by the reported model.

The reported ANN training history covers 1,400 epochs, with separate training and test diagnostics, regression coefficients, and MSE trajectories presented in Figure 10. Together with the formal input vector, output target, MSE fitting objective, and BIM aggregation equations, these elements provide the model specification used to interpret the reported results. For replication-oriented implementations, reporting the full ANN architecture, activation functions, data-partition ratio, normalization/scaling specification, MATLAB release/toolbox configuration, and random seed would further standardize exact computational reproduction.

For mathematical clarity, the prediction mapping is

$$\hat{p}(m,t) = f_\theta\big(x(m,t)\big), \qquad x(m,t) = \big[Y(t),\ M(t),\ c(m)\big]^T, \tag{3}$$

where $\hat{p}(m,t)$ denotes the ANN-predicted unit cost of material $m$ at time $t$ and $\theta$ denotes the fitted network parameters. The project-level forecast at completion date $T$ is then obtained by combining the material/item predictions with BIM quantities as

$$\hat{C}(T) = \sum_j q_j\,\hat{p}_j(T), \tag{4}$$

where $q_j$ is the BIM-derived quantity for item $j$. These equations describe the actual deterministic ANN–BIM computation used in the manuscript; generic ANFIS equations and fuzzy-rule schematics are not used to characterize the reported results.

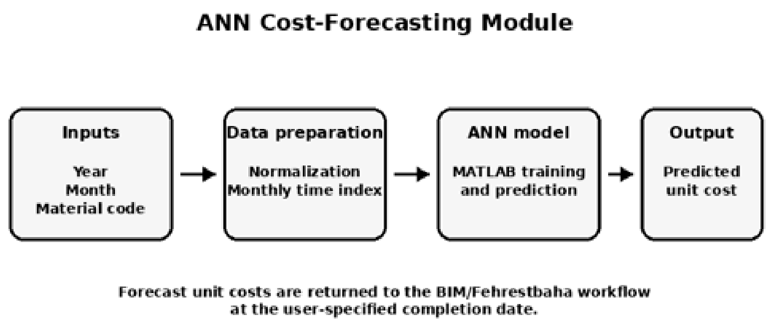



**Figure 9:** Input–output structure of the ANN cost-forecasting module

**Step 4. Displaying and evaluating the results of the trained ANN.** Figure 10 presents the ANN training/test regression diagnostics and mean squared error (MSE) trajectories for the historical material-cost dataset.

Figure 10 reports $R = 0.93976$ for the training subset and $R = 0.91111$ for the internal test subset, with declining MSE trajectories over the 1,400-epoch training history. These quantities are used as internal model-fit diagnostics. Because the monthly series contains values derived

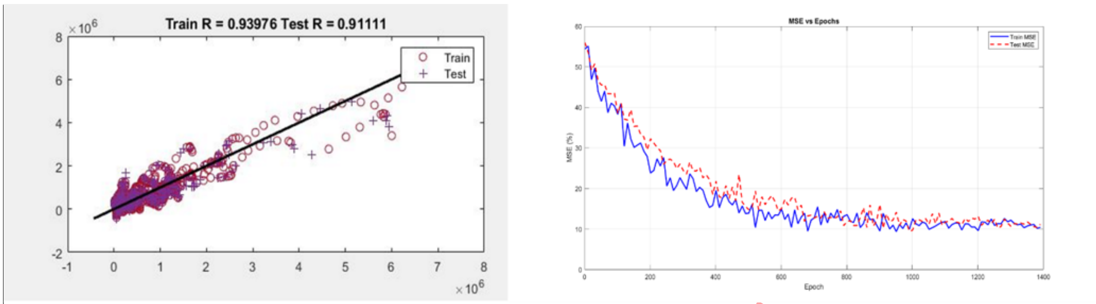



**Figure 10:** ANN training/test diagnostics for the historical material-cost dataset

from temporally resampled quarterly indices, the diagnostics are interpreted conservatively rather than as a standalone independent time-series validation. The principal project-level temporal check is the December 2023 case, which lies beyond the 2013–2022 model-development horizon. Accordingly, validation is reported at two complementary levels: internal ANN diagnostics (training/test $R$ and MSE trajectories) and project-level error measures against the actual December 2023 cost, summarized in Table 4.

### 2.5 Phase 5: Forecasting Project Cost at Completion

Phase 5 applies the trained ANN to a user-specified completion date, updates Fehrestbaha unit prices, and aggregates item costs using BIM-derived quantities.

#### 2.5.1 Entering the Project Completion Date

After linking Fehrestbaha items to the BIM model, each forecast record uses the same input vector defined in Section 2.4.3: target year, target month, and material identifier. For each of the sixteen material identifiers, the ANN returns a deterministic predicted unit cost at the specified completion date. “Calendar type” is not treated as a separate model input.

#### 2.5.2 Predicting Fehrestbaha Item Costs with the ANN at Project Completion

To predict future costs, the ANN combines the user-defined target year and month with each material code and estimates the corresponding unit price at project completion. Percentage escalation relative to the initial Fehrestbaha rate is then derived from the predicted and baseline prices. The model therefore provides a material-specific completion-date price vector that can be returned to the BIM cost database.

### 2.5.3 Predicting Total Project Cost at Completion

Once completion-date Fehrestbaha unit prices are obtained, they are integrated into the BIM database and combined with BIM-derived quantities. For item $j$ at completion date $T$, the predicted item cost is $q_j \times \hat{p}_j(T)$, and the total predicted project cost is $\hat{C}(T) = \sum_j q_j \hat{p}_j(T)$, as in Equation (4), where $q_j$ is the BIM-derived quantity and $\hat{p}_j(T)$ is the ANN-predicted unit price. Each quantity is evaluated in the unit specified by the corresponding Fehrestbaha item (for example, m$^3$ for volumetric concrete). The aggregation is repeated over all mapped items to obtain the final project-cost forecast.

**Developed plug-ins.**

- The first imports Fehrestbaha data into the BIM environment.
- The second estimates construction costs using Fehrestbaha items at project start.
- The third predicts item costs at project completion using end-date input and ANN-based cost data.
- The last computes total project cost at completion.

Figure 11 shows the developed plug-ins.

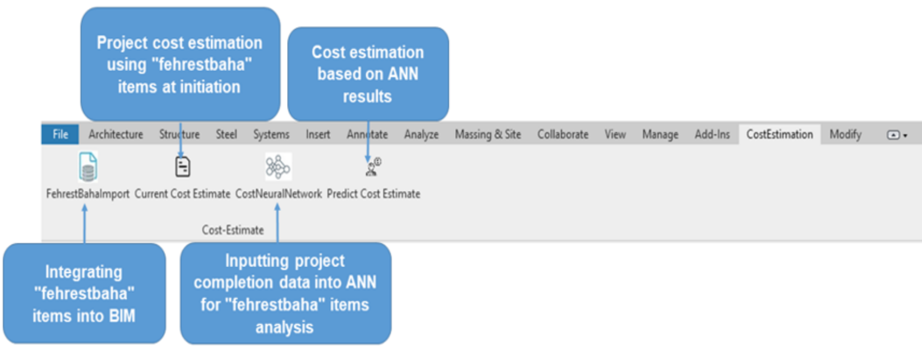



**Figure 11:** Developed plug-ins in the model

## 3 Results

### 3.1 Case Study and Model Validation

The empirical evaluation was conducted on a single nine-story residential building in northwest Tehran, comprising one parking floor and eight residential floors with four units per floor, each approximately 449.861 $m^2$ (Figure 12). The case is used as a proof-of-concept for the integrated workflow and does not constitute external validation across building types, regions, or market regimes.

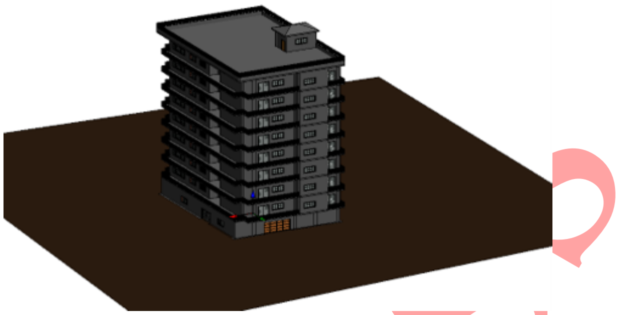


**Figure 12:** 3D view of the building in the BIM model

The project started in April 2022 and finished in December 2023. Fehrestbaha items from 2022 were integrated into the BIM model to calculate the initial project cost, and the actual completion date (December 2023) was then entered as the target date for ANN forecasting in the BIM environment (Figure 13).

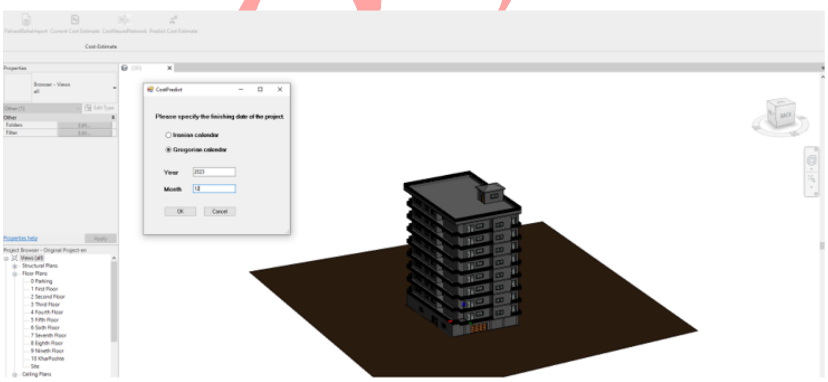



**Figure 13:** Entering the project completion date in the BIM environment

Figure 14 presents material unit-cost changes between the project start and completion dates. In this case, reinforcement and concrete increased by approximately 59% (about 110,000 Rials/kg) and 49% (about 3,315,000 Rials/$m^3$), respectively. Table 2 reports reinforcement in kg, concrete in $m^3$, and ceramic in $m^2$, consistent with the measurement basis used in the cost records; numerical separators are presented consistently throughout the table.

Figure 15 and Table 3 compare the actual final project cost $A_i$ with the April 2022 initial estimate $I_i$ and the ANN-based December 2023 estimate $P_i$. The signed percentage deviations in Table 3 are defined as

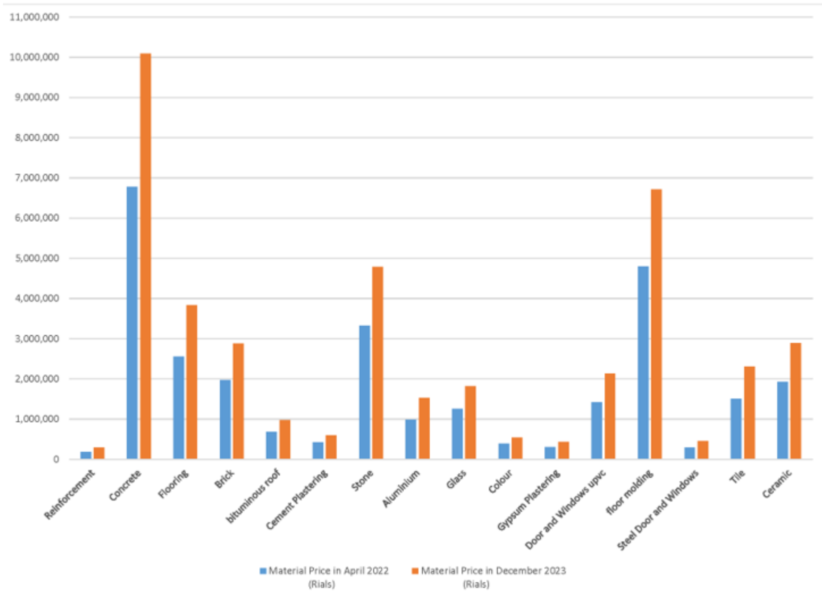



**Figure 14:** Cost increase of each material from project start to end dates



**Table 2:** Results of the increase in the cost of each material at the start and end dates of the project

| Material Name | Unit | Material Price in Apr. 2022 (Rials) | Material Price in Dec. 2023 (Rials) | Increase Ratio |
|---|---|---|---|---|
| Reinforcement | kg | 186,500.000 | 296,535.953 | 1.59 |
| Concrete | $m^3$ | 6,780,000.000 | 10,095,420.562 | 1.489 |
| Flooring | $m^2$ | 2,553,000.000 | 3,829,500.624 | 1.50 |
| Brick | $m^2$ | 1,975,000.000 | 2,883,501.958 | 1.46 |
| Bituminous roof | $m^2$ | 680,000.000 | 972,400.869 | 1.43 |
| Cement plastering | $m^2$ | 426,500.000 | 592,408.557 | 1.389 |
| Stone | kg | 3,326,000.000 | 4,789,442.699 | 1.44 |
| Aluminium | $m^2$ | 988,500.000 | 1,532,175.658 | 1.55 |
| Glass | $m^2$ | 1,257,000.000 | 1,822,650.432 | 1.45 |
| Colour | $m^2$ | 386,000.000 | 538,471.690 | 1.395 |
| Gypsum plastering | kg | 298,500.000 | 432,825.852 | 1.45 |
| Door and windows UPVC | $m^2$ | 1,415,000.000 | 2,136,650.685 | 1.51 |
| Floor molding | kg | 4,792,000.000 | 6,708,802.635 | 1.40 |
| Steel door and windows | $m^2$ | 291,500.000 | 457,655.768 | 1.57 |
| Tile | $m^2$ | 1,509,000.000 | 2,308,770.176 | 1.53 |
| Ceramic | $m^2$ | 1,927,000.000 | 2,886,646.241 | 1.498 |

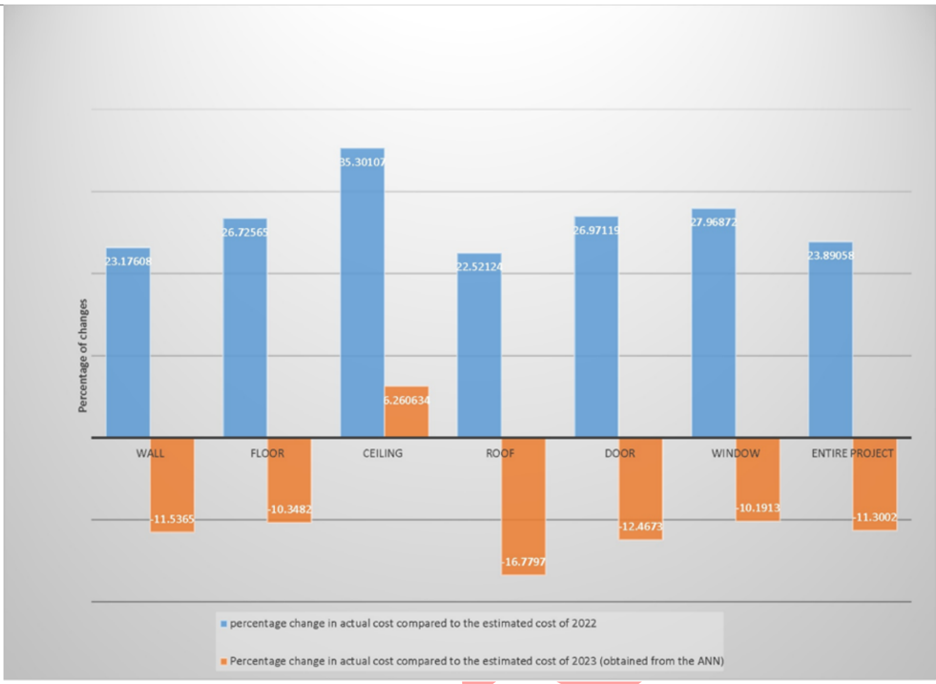



**Figure 15:** Comparison of actual project cost with ANN-predicted final cost and 2022 estimate

$$E_i(\text{initial}) = \frac{100\,(A_i - I_i)}{A_i} \quad \text{and} \quad E_i(\text{ANN}) = \frac{100\,(A_i - P_i)}{A_i}.$$

Positive values indicate underestimation relative to the actual cost, whereas negative values indicate overestimation. Absolute percentage deviation is $|E|$. The April 2022 estimate is used as an operational no-update baseline; it is not presented as an independently fitted statistical forecasting model.

**Table 3:** Comparison of the actual project costs with the costs predicted by ANN at the end of the project and estimated cost in 2022

| Element Name | Actual Project Cost (Rials) | Estimated Cost in Apr. 2022 (Rials) | Estimated Cost in Dec. 2023 Using ANN (Rials) | $E_i$(initial) (%) | $E_i$(ANN) (%) |
|---|---|---|---|---|---|
| Wall | 341,418,272,000 | 262,290,884,771.975 | 380,806,142,084.116 | 23.176 | −11.537 |
| Floor | 27,975,667,000 | 20,498,988,706.382 | 30,870,649,311.468 | 26.726 | −10.348 |
| Ceiling | 4,146,687,000 | 2,682,861,938.285 | 3,887,078,117.143 | 35.301 | 6.261 |
| Roof | 2,920,979,000 | 2,263,138,396.282 | 3,411,109,992.811 | 22.521 | −16.780 |
| Door | 17,823,638,000 | 13,016,390,504.119 | 20,045,765,871.086 | 26.971 | −12.467 |
| Window | 16,283,002,000 | 11,728,854,995.453 | 17,942,455,625.943 | 27.969 | −10.191 |
| **Entire Project** | **410,568,245,000** | **312,481,119,312.496** | **456,963,201,002.566** | **23.891** | −11.300 |

Among components, the roof shows the highest deviation in ANN estimates (under 17%, approximately 490 million Rials), while the ceiling has the highest accuracy (about 6%, approximately 260 million Rials). At project completion, actual cost deviations from initial estimates range between 23% and 35%, with the roof showing the lowest change (approximately 658 million Rials) and the ceiling the highest (approximately 1.464 billion Rials).

For numerical transparency, descriptive error metrics were calculated across the six reported BIM element categories (wall, floor, ceiling, roof, door, and window). The April 2022 estimate is treated here as a no-update operational baseline rather than as a competing statistical forecasting model. For $n$ elements with actual cost $A_i$ and estimate $P_i$:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|A_i - P_i|, \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - P_i)^2}, \tag{6}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\frac{|A_i - P_i|}{A_i}, \tag{7}$$

$$\mathrm{WMAPE} = 100\,\frac{\sum_{i=1}^{n}|A_i - P_i|}{\sum_{i=1}^{n}A_i}. \tag{8}$$

The ANN estimate reduces all four descriptive error measures (Equations (5)–(8)) relative to the no-update baseline in this case. These metrics provide the operational comparison requested for the reported project and summarize the six BIM element categories included in Table 3. The April 2022 initial estimate therefore serves as the study's transparent operational baseline rather than as a statistical benchmark model. A broader comparative study using independently fitted naïve, regression, time-series, or alternative machine-learning models under a common temporal-validation protocol would provide an additional benchmarking layer.

At project level, using the actual final cost as the denominator, the April 2022 initial estimate has a signed deviation of 23.891%, whereas the ANN-based December 2023 estimate has a signed deviation of $-11.300\%$ and an absolute deviation of 11.300%. Thus, the ANN estimate is closer to the actual total for this case. This comparison is descriptive: no inferential significance test is implied and no claim of optimal model selection is made.

## 4 Discussion

Inflation, material and equipment price fluctuations, and exchange-rate variation are established cost drivers in volatile construction markets. In the present single-project application, official Iranian adjustment indices captured a marked increase in material-related costs between April 2022 and December 2023. Reinforcement and concrete, among the high-volume inputs in the case building, exhibited substantial price escalation. These observations should not be generalized to all project types because the magnitude and composition of escalation depend on project location, specification, procurement timing, and the prevailing price regime.

In this case, the ANN–BIM workflow produced a completion-date estimate closer to the actual final cost than the April 2022 no-update estimate. The result supports the feasibility of returning time-indexed unit-cost forecasts to the BIM cost workflow. The present evidence is therefore interpreted at the project level, while broader comparative and probabilistic evaluation remains a natural extension of the framework. The same computational linkage can also support scenario-based recalculation when completion dates or BIM quantities change.

The workflow also provides several decision-support extensions that follow directly from the implemented BIM–cost linkage:

- Changing the target completion date generates alternative deterministic cost forecasts that can support cash-flow planning and schedule-related cost assessment.
- When a design modification changes BIM quantities, the revised quantities can be propagated through the same cost-calculation workflow to evaluate the resulting project-cost effect.
- Time-varying adjustment-index information reduces reliance on a static start-date estimate; probabilistic prediction intervals and scenario-based uncertainty propagation represent complementary extensions to the current deterministic formulation.

**Table 4:** Descriptive component-level error metrics for the initial no-update baseline and ANN completion-date estimate

| Estimate | MAE (billion Rials) | RMSE (billion Rials) | MAPE (%) | WMAPE (%) |
|---|---|---|---|---|
| April 2022 initial no-update baseline | 16.348 | 32.567 | 27.111 | 23.891 |
| ANN completion-date estimate | 7.819 | 16.165 | 11.264 | 11.427 |

Within the scope of this proof-of-concept, integrating BIM-derived quantities with official adjustment indices provides a structured decision-support workflow for completion-date cost assessment. Transferability can be examined by applying the same item-mapping logic to additional projects, market conditions, and compatible national cost systems.

## Limitations and Validation Boundaries

The study has seven principal scope boundaries. First, empirical evaluation uses one nine-story residential building in northwest Tehran and one 2022–2023 price regime, so the reported error measures are case-specific. Second, the model-development window spans 2013–2022, and performance under future structural breaks should be examined in additional time periods. Third, monthly temporal resampling of quarterly adjustment indices introduces dependence among adjacent values; Figure 10 is therefore interpreted as an internal diagnostic, while the

December 2023 case provides the principal post-development temporal assessment. Fourth, integer material identifiers act as categorical labels, and alternative categorical representations should be compared in future encoding-sensitivity analyses. Fifth, Table 4 compares the ANN with the operational no-update estimate; a broader benchmark suite would provide additional evidence on relative forecasting performance. Sixth, the ANN produces deterministic point forecasts rather than probabilistic prediction intervals. Seventh, Fehrestbaha coding and adjustment indices are specific to the Iranian statutory estimation system, so transferability should be evaluated across additional projects and cost systems. These boundaries define the intended proof-of-concept scope and provide a clear pathway for broader validation.

Future validation should apply a strict chronological holdout or rolling-origin design at the native quarterly-data level before monthly temporal alignment. Comparative tests should evaluate alternative categorical material representations and benchmark the ANN against naïve and deterministic adjustment-index forecasts, regression models, standard time-series methods, conventional ANN alternatives, and any proposed neuro-fuzzy model under the same temporal splits. Full ANN architecture and preprocessing specifications should be reported for replication-oriented studies. Prediction intervals or scenario-based uncertainty propagation, together with multi-project external validation, would further strengthen the evidence base.

These extensions would strengthen temporal validation, comparative benchmarking, reproducibility, and external validity while preserving the present study's central contribution: end-to-end integration of official cost information, ANN forecasting, Revit plug-ins, and BIM quantity aggregation.

## 5 Conclusion

This study developed a BIM-integrated ANN workflow that links Fehrestbaha item data and official adjustment indices to deterministic completion-date construction-cost forecasting. In the single Tehran residential case, the April 2022 initial estimate had a 23.891% signed deviation from the actual final cost, whereas the ANN-based December 2023 estimate had an absolute deviation of 11.300%. Component-level MAE, RMSE, MAPE, and WMAPE were also lower for the ANN estimate than for the no-update baseline. These results demonstrate proof-of-concept feasibility for this project but do not establish statistically significant superiority, probabilistic uncertainty handling, or universal predictive accuracy. The principal contribution is the operational linkage among statutory item coding, historical adjustment-index information, ANN forecasting, Revit plug-ins, and BIM quantity aggregation. The study does not present a project optimization model and therefore makes no optimization claim. Future validation can extend the current evidence through chronological or rolling-origin evaluation, categorical-encoding comparisons, fully documented model configuration, independent forecasting benchmarks, probabilistic uncertainty analysis, and testing across multiple projects and market regimes.

## Declarations

### Availability of Supporting Data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### Funding

The author received no specific funding for this research.

### Conflict of Interest

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

### Authors Contributions

**Hossein Jahangiri:** Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. **Pooria Rashvand:** Conceptualization, Methodology, Formal Analysis, Supervision, Writing – Review & Editing, Project Administration. **Nima Amani:** Investigation, Resources, Data Curation, Writing – Review & Editing. **Ahmad Shokouhfar:** Formal Analysis, Investigation, Writing – Review & Editing. **Reza Farokhzad:** Resources, Investigation, Writing – Review & Editing. All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

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