



REPUBLIC OF TÜRKİYE
ALTINBAŞ UNIVERSITY
Institute of Graduate Studies
Civil Engineering

**ESTIMATION AND ANALYSIS OF
BUILDING COSTS USING ARTIFICIAL
INTELLIGENCE SUPPORT VECTOR
MACHINE**

Zahra Salahaldain ABDULJABAR

Master's Thesis

Supervisor

Assoc. Prof. Dr. Sepanta NAİMİ

Istanbul, 2022

ESTIMATION AND ANALYSIS OF BUILDING COSTS USING ARTIFICIAL INTELLIGENCE SUPPORT VECTOR MACHINE

Zahra Salahaldain ABDULJABAR

Civil Engineering

Master's Thesis

ALTINBAŞ UNIVERSITY

2022

The thesis titled ESTIMATION AND ANALYSIS OF BUILDING COSTS USING ARTIFICIAL INTELLIGENCE SUPPORT VECTOR MACHINE prepared by ZAHRA SALAHALDAIN ABDULJABAR and submitted on 23/12/2022 has been **accepted unanimously** for the degree of Master of Science in Civil Engineering.

Assoc. Prof. Dr. Sepanta NAİMİ

Supervisor

Thesis Defense Committee Members:

Assoc. Prof. Dr. Sepanta NAİMİ

Department of Civil
Engineering,

Altınbaş University

Asst. Prof. Dr. Mohsen SEYEDİ

Department of Civil
Engineering,

Altınbaş University

Asst. Prof. Dr. Kaveh DEHGHANIAN

Department of Civil
Engineering,

İstanbul Aydın University

I hereby declare that this thesis meets all format and submission requirements of a Master`s Thesis.

Submission date of the thesis to the Graduate Education Institute: ____/____/____

I hereby declare that all information presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.



Zahra Salahaldain ABDULJABAR

Signature

DEDICATION

I thank my family, especially my mother and my father, for always standing by my side and supporting me throughout the study period.



PREFACE

I might want to thank my administrator: Assoc. Prof. Dr. Sepanta NAIMİ Please let me express my profound feeling of appreciation and gratefulness to both of you for the information: direction and unrestricted help you have given me. I want you to enjoy all that life has to offer and further achievements and accomplishments throughout your life.



ABSTRACT

ESTIMATION AND ANALYSIS OF BUILDING COSTS USING ARTIFICIAL INTELLIGENCE SUPPORT VECTOR MACHINE

ABDULJABAR, Zahra

M.Sc., Civil Engineering, Altınbaş University,

Supervisor: Assoc. Prof. Dr. Sepanta NAİMİ

Date: December / 2022

Pages: 131

An essential component of the building feasibility assessment is the conceptual cost estimate. In actuality, it is carried out based on the estimator's prior expertise. However, budgeting and cost control are planned and carried out ineffectively as a result of inaccurate cost estimates. To increase conceptual cost accuracy throughout the early stages of a project's life cycle in the construction sector, the goal of this article is to present an intelligent model. A support vector machine model, which is computationally effective, is created to calculate the conceptual costs of building projects. To get accurate estimates, the suggested neural network model is trained using a cross-validation method. Through the research of the literature and interviews with experts, the cost estimate's influencing elements are determined. As training instances, the cost information from 40 structures is used. Two commercial methods Nonlinear Regression (NR) and Evolutionary Fuzzy Neural Interface Model (EFNIM) are offered to illustrate how well the suggested model performs. Based on the readily accessible dataset from the relevant literature in the construction business, their results are contrasted. The computational findings show that the intelligent model that is being provided outperforms the other two potent methods. During the planning and conceptual design phase, the inaccuracy is satisfied for a project's conceptual cost estimate. Case studies demonstrate how SVMs

may help planners anticipate the cost of construction in an effective and precise manner.

Keywords: Building Cost; Conceptual Cost Estimation; Support Vector Machines; Cross-validation



TABLE OF CONTENTS

	<u>Pages</u>
ABSTRACT	vii
LIST OF TABLES	xiii
LIST OF FIGURES	xiv
ABBREVIATIONS	xvi
1. INTRODUCTION	1
1.1 GENERAL	1
1.2 BUILDING COST-EFFECTIVE FACTORS	2
1.3 COST ESTIMATION METHODS	3
1.4 RESEARCH PROBLEM	4
1.5 RESEARCH PROGRAM OBJECTIVES	4
1.6 ORGANIZATION OF THESIS	5
2. BASIC CONCEPTS AND LITERATURE REVIEW	6
2.1 GENERAL	6
2.2 REQUIREMENTS OF ESTIMATION COST	6
2.3 RANK OF CONSTRUCTION COST ESTIMATION	7
2.3.1 Challenges in Construction Cost Estimation	8
2.3.2 Producing an Accurate Estimate.....	8
2.3.3 Material Cost	8
2.3.4 Labor Charges.....	8
2.3.5 Precise Takeoffs	9
2.4 CONSTRUCTION COST ESTIMATION FORMATS.....	9

2.5 BID ESTIMATION	10
2.6 COST ESTIMATION APPROACHES	10
2.6.1 Unit Valuation	10
2.6.2 Cost for Square Foot.....	11
2.7 PRICE ESTIMATION ACCURACY FOR PROJECTS	11
2.7.1 Expert Ruling Method	11
2.7.2 Comparable Estimating Technique	11
2.7.3 Approximating Data	12
2.7.4 The Bottom-up Estimation Technique	12
2.7.5 The Three-Point Estimation Technique.....	12
2.7.6 Decision-Making Process	13
2.8 BENEFITS OF COST ESTIMATION.....	13
2.9 RISK ELIMINATION IN CONSTRUCTION	14
2.9.1 Strategies for Risk Factor	15
2.9.2 Risk-Related Concerns with Cost Estimating	16
2.10 LITERATURE SURVEY	16
2.11 SUMMARY OF PREVIOUS STUDIES	25
2.12 CURRENT STUDY CONTRIBUTION	26
3. METHLODOGY AND MODEL BUILT	31
3.1 GENERAL	31
3.2 CONSTRUCTION PRODUCTIVITY FACTORS.....	33
3.2.1 Labor Productivity	33
3.2.2 Equipment Productivity	36
3.3 CASE STUDY OBSERVATION	40

3.3.1 Applying Revit Drawing	41
3.4 PROPOSED SUPPORT VECTOR MODEL	48
3.4.1 Support Vector Machine.....	49
3.4.2 Cross-Validation Technique	52
3.4.3 Steps of Proposed Intelligent Model	53
3.5 EVOLUTIONARY FUZZY NEURAL INTERFACE MODEL	56
3.6 MODEL VALIDATION	57
4. RESULTS AND DISCUSSION.....	61
4.1 COLLECTING DATA	61
4.2 QUESTIONNAIRE RESULTS.....	62
4.3 LABOR PRODUCTIVITY RESULTS.....	62
4.4 EQUIPMENT PRODUCTIVITY RESULTS	70
4.4.1 Equipment Productivity Factors Effect	71
4.5 EFFICIENT SVM RESULTS	78
4.5.1 Proposed Model Validation	79
4.5.2 Results of Cost Estimation Process	85
5. CONCLUSIONS AND RECOMMENDATIONS	89
5.1 GENERAL	89
5.2 CONCLUSIONS	89
5.3 RECOMMENDATIONS FOR FUTURE STUDIES.....	90
REFERENCES.....	92
APPENDIX A: ESSENTIAL BILL OF WALL QUANTITIES	101
APPENDIX B: ESSENTIAL BILL OF FLOOR QUANTITIES	107
APPENDIX C: ESSENTIAL BILL OF DOOR QUANTITIES	108

APPENDIX-D: ESSENTIAL BILL OF WINDOW QUANTITIES	114
APPENDIX-E: MATLAB CODE.....	120



LIST OF TABLES

	<u>Pages</u>
Table 4.1: The Distribution of Questionnaires.....	62
Table 4.2: The independent factors for Labor productivity	63
Table 4.3: Equipment productivity factors.....	71
Table 4.4: SVM results of ranking factors.	78
Table 4.5: Patterns for conceptual estimation of building cost.	80
Table 4.6: Description of qualitative factors for conceptual cost estimating.....	82
Table 4.7: Overall comparative results.	84
Table 4.8: Cost estimation of the case study.....	86

LIST OF FIGURES

	<u>Pages</u>
Figure 2.1: Subjective Uncertainty Boundary Interpretation and Tail Extension for 70% Confidence Interval Applied to Subject Matter Expert Elicitation.	13
Figure 2.2: Sample recommendations about use of risk analysis techniques.	15
Figure 2.3: General model of SVM.....	17
Figure 2.4: Comparison of the deviation between the predicted and actual values of construction cost of the whole process of the system.	20
Figure 2.5: EAC prediction model.	23
Figure 3.1: Walls with the dimensions of the case study building.....	42
Figure 3.2: Applying the families of doors and windows.	43
Figure 3.3: 3D of the first floor.	44
Figure 3.4: Assembly group of the first level of the building.	45
Figure 3.5: Applying building levels.....	46
Figure 3.6: Adding the non-symmetrical elements to the building.....	47
Figure 3.7: Nonlinear SVM.....	49
Figure 3.8: The proposed LS-SVM model.	55
Figure 3.9: EFNIM Architecture	57
Figure 4.1: Distribution of questionnaire percentage.....	62
Figure 4.2: Work scheduling factor effect on quantity per floor.	64
Figure 4.3: Work scheduling factor effect on Floor height.....	65

Figure 4.4: Number of supervisor factor effect on quantity per floor.....	66
Figure 4.5: Number of supervisor factor effect on Floor height	66
Figure 4.6: Workers experience factor effect on quantity per floor.....	67
Figure 4.7: Workers experience factor effect on Floor height.	68
Figure 4.8: Change task type factor effect on quantity per floor	69
Figure 4.9: Change task type factor effect on Floor height.....	69
Figure 4.10: Equipment availability factor effect on quantity per floor	72
Figure 4.11: Equipment availability factor effect on Floor height.....	72
Figure 4.12: Equipment scheduling efficiency factor effect on quantity per floor.	73
Figure 4.13: Equipment scheduling efficiency factor effect on Floor height.	74
Figure 4.14: Suitability of equipment to site requirements factor effect on quantity per floor.	75
Figure 4.15: Suitability of equipment to site requirements factor effect on Floor height....	75
Figure 4.16: Maintenance quality factor effect on quantity per floor.	77
Figure 4.17: Maintenance quality factor effect on Floor height.	77
Figure 4.18: Results of SVM ranking factors.	79
Figure 4.19: Comparison of accuracy for proposed model, EFNIM, and NL cost estimation models.	84
Figure 4.20: Pictorial representations of the proposed model and other two famous techniques.....	85
Figure 4.21: The case study cost estimation.	86

Figure 4.22: The differences in walls construction cost under factors effect. 87

Figure 4.23: The differences in floor construction cost under factors effect. 87



ABBREVIATIONS

ANN	:	Artificial Neural Network
CAD	:	Computer-Aided Design
BIM	:	Building Information Modelling
CM	:	Construction Managers
POP	:	Public Offering Price
SI	:	International System of Units
PCA	:	Principal Component Analysis
SVM	:	Support Vector Machine
RMSE	:	Root Means Square Error
MAPE	:	Mean Absolute Percentage Error
RBFNN	:	Radial Basis Function Neural Network
CBR	:	Case-Based Reasoning
RA	:	Regression Analysis
PSO	:	Particle Swarm Optimization
DT	:	Decision Tree
BEE	:	Bureau of Energy Efficiency
SCPE	:	System of Classification of Processes of Execution
SCPB	:	System of Classification of Basic Processes
EFNIM	:	Evolutionary Fuzzy Neural Interface Model

1. INTRODUCTION

1.1 GENERAL

Building conceptual cost estimates give planners a basis for assessing the project's viability at the conceptual planning stage. The feasibility and profitability of a project are both significantly impacted by erroneous cost estimation. Low feasibility prevents clients from selling their existing projects because of overestimated expenses. On the other side, an underestimated cost can deceive planners into believing it is very feasible, which would result in extra expenditures for the customer at the building stage. Overestimated or underestimated expenses, therefore, have an impact on clients' earnings, necessitating the use of an accurate measurement technique [1].

The sum of fixed and variable costs equals the value or total amount of money needed to accomplish the work or run a firm. Cost estimation is defined as the determination of a project's most likely cost. The project's scope must be determined. The size of the projects, their diversity in terms of technology, materials, and products, and the designer's experience with them all play a role in project importance [2]. Project information managers are architects or constructors who are in charge of a project. Coordination issues arise, however, because the information may be misunderstood or misinterpreted by members of the design team. Another source of unresolved conflicts could be schematic documentation that has not been updated in accordance with coordination meeting decisions. In. This means that cost models should be accurate in their predictions, user-centered in their efficiency, and long-lasting enough to account for cost variance variables[3]. In addition, the cost of a building project must be estimated within a certain range of accuracy. The biggest roadblocks to a cost estimate, especially in the early stages, are a lack of preliminary data and increased uncertainty due to engineering solutions. Quantity calculation is done if the planning process is far enough that the job description can be determined, however early planning may not be based on quantity calculations. To acquire an accurate estimate, selecting precise price estimation methods necessitates more detailed guidelines and a significant amount of time[4].

1.2 BUILDING COST-EFFECTIVE FACTORS

Experience is the main focus of conceptual cost estimate. Cost estimators are limited to basing their construction cost estimates during the conceptual planning phase on the initial design and project concepts. Cost estimators consult past situations when there is little information, and they then assess the conceptual cost in light of their prior experiences [5]. Nevertheless, a wide range of factors affect building costs. Some of these characteristics, including geological property and decorative class, are rife with ambiguity [6]. Estimators cannot correctly estimate building costs using a simple linear method since the evaluation process is so complicated and imprecise. Because of this, current building cost estimates are imprecise.

One of the most serious issues in the building sector is the disparity between the expected cost and the actual bill. It's critical to have accurate cost estimates for engineering and construction projects. Before the detailed design and contract particulars are established, this method generates an estimate of the likely cost of a proposed project [7]. As a result, a cost estimate is an important document that assists the client in doing a thorough analysis of the viability of his proposed project in order to determine whether the investment is worthwhile.

A professional estimating firm should give the estimates, either as part of the design team or directly for the owner. However, a fundamental issue limiting empirical progress in price forecasting is a lack of theories on building price forecasting. Building cost estimates should be established during the project's initial design stage. Cost estimates often become more precise and detailed when more information about the site characteristics and suggested solutions is obtained[8]. There are various important factors that influence the cost of a structure. One of the most difficult aspects of developing the model is choosing the most influential factors. As a result, several scholars researched these factors and constructed their models based on them.

1.3 COST ESTIMATION METHODS

There are various types of research to estimate the conceptual cost of construction projects in the associated literature. Neural networks (NNs) have received a lot of attention in this sector, especially in the previous 10 years. An evolutionary conceptual cost estimation model for buildings was created using the Evolutionary Fuzzy Neural Inference Model (EFNIM). In the model, fuzzy input-output mapping is handled by neural networks, fuzzy logic is utilized to represent uncertainty and approximate reasoning, and genetic algorithms are predominantly employed for optimization. However, it takes a very considerable amount of time to conduct the computation to find the best answer [9]. Support vector machines (SVMs), a kind of artificial intelligence, were used to forecast the conceptual cost of building [10]. The SVM model was introduced for assessing the accuracy of conceptual cost estimates, and its use in the construction industry was looked at [6]. It was suggested to anticipate the cost of the construction project using an intelligent strategy based on the SVM. The outcomes demonstrated that the least square SVM's prediction accuracy was superior to the NN [11].

The appropriateness of any given estimating method depends typically on the purpose for which it is employed, the quantity of information available at the time of the estimation, and the person utilizing it. Although customers and contractors rely on existing cost prediction and forecasting techniques, real final building project prices still differ significantly from initial projections [7]. To suggest a general copula-based Monte Carlo simulation approach for forecasting the overall costs of building projects with dependent cost components. It was discovered that various dependency structures might produce various total cost probability distributions. Moreover, it is discovered that the current goodness of fit tests may be used to choose the copula that performs the best. The article concluded that the copula-based Monte Carlo simulation approach may reasonably anticipate the overall cost of construction projects [7 and 9]. Salunkhe and Priti [12] contrast the precision of several estimation methodologies. By completing construction cost estimations using linear regression analysis (LRA) and supporting vector machine techniques (SVMs), the results highlight the urgent need for a solution to the problem of cost overruns.

1.4 RESEARCH PROBLEM

Awareness of the cost structure of construction works based on previously finished construction buildings is an important element of estimating and controlling the costs on similar future projects. The recognizable structure makes planning and monitoring of construction costs simpler but less accurate. Due to this prominence of cost estimate in early stage and limited availability of information during the early phase of a project, construction managers typically leverage their knowledge, experience and standard estimators to estimate project costs.

To enhance the decision-making process in feasibility studies under the influence factors of a construction building, a novel intelligent model for building projects based on an SVM model is implemented in this study. The suggested approach may be successfully used to anticipate conceptual costs over the long run in the building sector. In the SVM model, a cross-validation procedure is also used on the training dataset to minimize overfitting and to generate accurate results. The available information from the relevant literature in the construction sector is used to evaluate the suggested intelligent model's accuracy in estimating the expenses of these projects. The applicability and usefulness of the suggested approach are further demonstrated by comparisons with other well-known methodologies.

1.5 RESEARCH PROGRAM OBJECTIVES

The main objectives of this study are:

- a. To identify the influential factors for the construction building process.
- b. To utilize the coupled Revit Software and AutoCAD software for estimating the cost of multi-Story building.
- c. To develop an artificial intelligent model based on cross-validation, using the support vector machine (SVM) method, to support early estimates of total construction costs of construction building.
- d. To validate the proposed model using forty different building in Central governorates of Iraq (Baghdad, Babil, Karbala and Najaf).

1.6 ORGANIZATION OF THESIS

This thesis has five chapters. Chapter one includes an introduction to the cost estimation in construction building project management. Chapter two presents a general view of the criteria for the selection of cost methods and parameters in different studies collected from vary research. The computational program, including the studied parameters and the work methodology, are presented in Chapter three. Chapter four discusses the result and the calculation of the work. Chapter five is the conclusion.



2. BASIC CONCEPTS AND LITERATURE REVIEW

2.1 GENERAL

The cost estimation is the method of trying to predict the total costs of an innovative building project. To be able to predict accurately, this is a critical component of something like a plan. Prior to actually proceeding with a project, a consultant should calculate a providers utilize of all the complex costs. It will help to define its program's variables, such as its scope, resources necessary, timeline, but also, of course, expenditure. While using accurate evaluation, the producer can ensure that they order the correct amount of materials while staying within their budget [13].

A purchasing bundle will almost always be directly related to the use of building implementation. This link ensures that suppliers purchase materials in the permitted amount and extent. Any deviation from the cost estimate computation would be instantly flagged in order to identify any possible losses or advantages. These forecasts may change based on the project's current stage. The amplitude instruction validates the scheme it before starts. It's the first phase, as well as the second stage is predicated on skilled decision and comparison professions. Independent commission using overall idea of the project as a starting point. Estimation [14].

A rough first estimate with a narrower strategy that is somewhat more realistic. Because of this assumption, many projects go over budget. This estimate takes into account the project's notions, goals, and deliverables. The builder then does provide a quote based on expected unit costs. Estimated final value: It is the final step of estimation, but it shaped once the consultant has identified the majority or all of actual costs involved the with plan. It's the most exact type of estimation method and is used to create tenders and bidding wars[15].

2.2 REQUIREMENTS OF ESTIMATION COST

Before calculating estimates, building estimators collect the necessary data in an irregularly uniform way. Regardless, the best estimating tactic must be chosen. Identifying the critical factors [16].

Estimation methods are the foundation of project management and success. Estimating unit prices is one method. Anywhere there's a cost involved with each component of effort, this same contractor could combine all of this information to make a guesstimate. Another method is to use sticks to approximate. The appraiser does have a list of expenses that have already been determined (materials, labor salaries, seller proposals). Using this list, the total costs are estimated. If indeed the estimator has enough data, they can indicate manually and get reasonably precise results. To electronically develop precise predictions, he requires a great deal of experience, expert knowledge, and understanding of construction[17].

2.3 RANK OF CONSTRUCTION COST ESTIMATION

A number of factors affect accurate building estimated cost. It's an important procedure that underscores how widely respected building projects are. The accuracy or inaccuracy of an estimate can make or break a company's financial performance. Nevertheless, there is indeed a high level of risk because of the various factors implicated, which can range from differing material values to unexpectedly high labor costs[18].

Tangible price differences have an immediate effect on the total cost of the program. Once planning anticipated expenses, the contractor wants to ensure that the costing is as accurate as possible. Build reseller addition updates provide true cost information to help contractors estimate costs as precisely as feasible at all times [19].

Through using real costs instead of average costs, the construction company can improve the precision and effectiveness of the price estimation method and competition. No one can really accommodate for construction projections to actually cost a business money. Every penny matters. Trying to make sure the approx. price levels and true cost match ensures that the contractor is watching so each dollar[20].

Since each profession has its own set of variables, producing a precise construction approximate necessitates practice, expertise, and reliable data. It remains one of the most difficult but crucial building skills [21].

2.3.1 Challenges in Construction Cost Estimation

Dangers in the building projects estimation method, such as estimating content costs and operational expenses incorrectly, will have a bad impact on the bottom line. Overestimation: causes the owner as well as client to overpay, trying to prevent the contractor from obtaining the role in the first place due to overblown pricing [22]

2.3.2 Producing an Accurate Estimate

Building cost estimates are among the riskiest aspects of the business's profitability and prospects to attract customers. He must be as precise as is reasonably possible. Numerous factors, such as markup, sub - contractor, labor, and physical cost, must be calculated. Here are other links for calculating an exact cost of the building [23].

2.3.3 Material Cost

The construction company will most probably have a positive idea of the material costs. Nevertheless, by the time the world construction begins, an estimate is lobbed off by the currency's shifting source materials and demands. It's critical to maintain solid communication with the providers because they know what kinds of products could be appropriate for the task [24].

2.3.4 Labor Charges

Job is perhaps the most difficult expenditure to approximate, with much more than one third of accused persons in an inquiry admitting to estimating labor price increases based on best speculations rather than actual data. It's the most expensive component of the project's overall cost. The contractor is obligated to pay wages, employee taxation, benefits (if applicable), and other expenses. There are several controls available to allow the contractor to make a contribution the cost of labor that best meets the needs. Risk must be assessed, and contingencies built into plans: Risks should be minimized, and contingencies built into plans. Items do not go as scheduled, so the construction company must plan for them all to ensure that the costs are recouped [25].

2.3.5 Precise Takeoffs

A thorough and precise departure affirms dependable physical parameters for the plan, which serves as the foundation for the best planning phase. Using software to execute a takeoff improves accuracy by reducing error rates which occurs when it is done manually [26].

Which was before meetings but also site visits are required for all initiatives, regardless of their size, because each worksite is unique and there isn't any guarantee that project would be similar in size to others completed by the contracting company. It is critical to obtain the undertrained of the land following road access to the overlapping space [27].

2.4 CONSTRUCTION COST ESTIMATION FORMATS

The first point to know is that a building estimated cost is just that: an estimate. Even as work proceeds, the construction company may encounter issues that raise the cost. In addition, hand, the contractor may discover ways to save resources. As both a result, it is common for a single project to receive multiple estimates over the period of its existence [28].

There are number of concepts of estimate according to the American Society of Professional Estimators. Each level offers a better level of component and is more accurate than the one before it [29]:

- a. A Sequence of Awesomeness Estimate is indeed a rough calculation that is only directionally accurate. A guesstimate can be used to determine the feasibility of a project, which isn't actually different.
- b. Level 2 is a Chart Design Estimate. This estimate was developed using the project's schematic. This data could be used by construction businesses to determine whether a prospective job is worth examining further.
- c. A Conceptual Design Estimation is just a preliminary estimate based on the original design.
- d. A Design Phase Estimation was created based on recommended plans and requiring large.

- e. Bid Guesstimate is the term given to the company's final estimate, which is premised on all obtainable building plans, drawings, and cost of materials. It is the final, definitive estimate that is provided to the client.

2.5 BID ESTIMATION

The person providing this final estimate, which is premised on all obtainable blueprints, illustrations, and cost of materials. It is the final, definitive estimate that is provided to the client. that poverty in order to determine whether a gantry or other endeavor is beneficial to a bridge. As the principle evolves, technicians can use the initial schematics to develop a more precise Estimation. This isn't destined to be a final number, but it provides a rough beginning for the contracting company [30].

Service providers rely their offer estimates just on specifics of the project design. Service providers take into account the cost of goods, labor, and other factors. Potential customers use these Estimations to determine which provider to hire. Control estimates are ongoing clearance estimates performed by the contracting company while the project is under construction. It acts similarly toward a budget in that the builder tracks total costs versus expenditures. This provides project managers with visibility, allowing them to control costs and reply to unforeseen circumstances [31].

2.6 COST ESTIMATION APPROACHES

2.6.1 Unit Valuation

The crucial factor that determines is the most widely used method of valuing various products and services. Unit cost estimating is useful for calculating straight costs. This same hourly rate for the work is determined by the contractor. The abundant components are valued per ton or pallet. By beginning with unit expenses, the construction company can skills that make the majority of the Estimation. All you'll have to do at that juncture is explain the indirect charges [32].

2.6.2 Cost for Square Foot

A quick estimate is more important than a precise unique. For example, square foot assessment can be misrepresentative because the benchmarks are calculated in meaningfully different ways. The benches, which are simply a collection of data sheets, offer statistical average cost information for each type of facility with a distribution. The contractor may be required to submit the bid by a specific deadline. A relatively short and uninteresting apology is all that is required in this situation. It may now appear to be risky for him to submit a broad, ballpark estimate as an official proposal. However, bids frequently lead to negotiations, and the customer has always been free to request a price reduction. Similarly, designers frequently scrimp during their first assignment. This entails resubmitting the proposal for editing. All of this goes to say that the price proposed by the contracting company would never exceed the total cost of the project. It works well enough to change along the way, possibly significantly. As a result, the construction company can get away with providing a rough estimate [33].

Prior to actually making an informed guess about a program's square footage, one should first take into account the project's core work scope. The benefit of this approach is that the contractor can submit far more quotes than he could with much more accurate estimates [34].

2.7 PRICE ESTIMATION ACCURACY FOR PROJECTS

2.7.1 Expert Ruling Method

Knowledge and experience from individuals or groups to particular experience or education in team and physiological reserve making plans and estimation is required. Evaluation process, steered by historical data, provides in-depth expertise about the surroundings as well as details from those other similar programs. Furthermore, analytical approach can be used to determine whether to syndicate different Prediction models and how to solve conflicts among people [35].

2.7.2 Comparable Estimating Technique

Comparable cost analysis uses values from a previous, similar project to estimate the same variable or dimension for just a current plan. The above values include context, cost, spending plan, as well as duration, as well as scale events such as size, load, as well as difficulty. This

method of cost prediction uses the actual costs of previous, comparable projects to calculate the cost of the current plan. It is most dependable when past projects are similar in reality however not in appearance, as this is when the team members who are attempting to create the estimates have had the necessary experience [36].

2.7.3 Approximating Data

Once estimating asset quantities for an action based on past information and project parameters, costing method employs an algorithm before establishing a statistical link between historical data and additional variables (such as square foot in building) [37].

2.7.4 The Bottom-up Estimation Technique

The squad and material assets are predicted at activity parity before being aggregated inside the Bottom-up Vaguely resembling Method to generate forecasts for work items, switch accts, and swift configurations are possible. Lowest-up estimation is a method for approximating an effort component. Prior to beginning actions, the cost of each individual 's work bundle is projected with the greatest degree of precision. The product and price are first summarized as well as rolled into higher levels for afterward reporting as well as subsequent actions. This same cost and precision of least expensive estimating are typically affected by the quantity as well as complexity of the each personal action or group of tasks [38].

2.7.5 The Three-Point Estimation Technique

By recognizing estimating uncertainty and risk and employing three points (Figure 2.1) to produce an estimated range for an action's cost, the accuracy of single-opinion activity cost estimates may be increased [39].

- i. Most likely (M): The cost of the action, based on an accurate assessment of the effort required to complete the work and slightly anticipated costs.
- ii. Optimistic (O): The price of the action is based on consideration of the best case scenario.
- iii. Negative (P): The activity's cost as determined by examination of the worst-case scenario.

2.7.6 Decision-Making Process

Preference methods include unanimity, large percentage, plurality, juncture dispersion, and dictatorial regime. For there to be agreement, an agreement must be reached. A vote is typically used to establish a majority or clear majority. To be considered valid, the choice must be acknowledged by a majority of the participants [40].

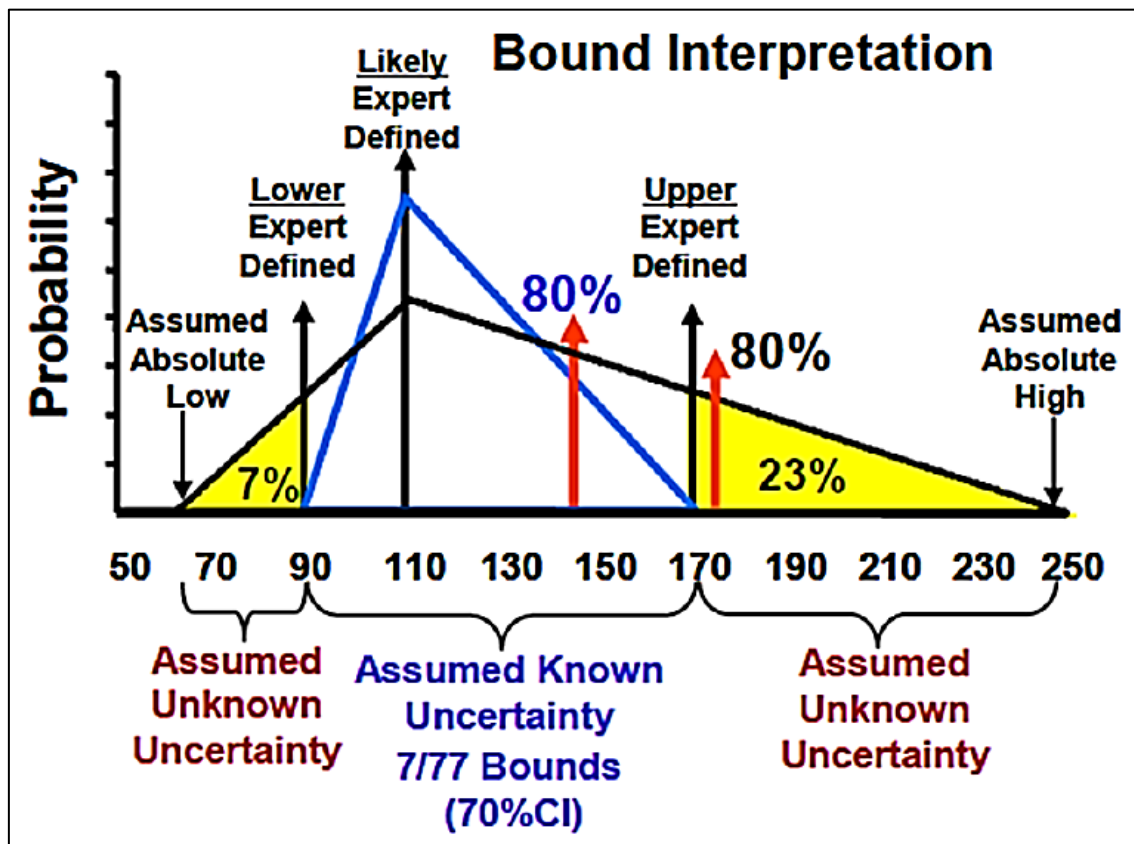


Figure 2.1: Subjective Uncertainty Boundary Interpretation and Tail Extension for 70% Confidence Interval Applied to Subject Matter Expert Elicitation [39].

2.8 BENEFITS OF COST ESTIMATION

The building industry has benefited greatly from the technological breakthroughs that have occurred over the last few decades, especially through the inventions provided by value estimate software. Building estimating software has unquestionably altered how experts

conduct business and achieve their goals. It provides a streamlined process that gives forward-thinking companies a competitive advantage. Construction estimating software packages have become increasingly user-friendly since their introduction to the market, allowing manufacturing professionals to select task-specific requests and then personally tailored operating systems to generate projections[41].

The building industry has benefited greatly from the technological breakthroughs that have occurred over the last few decades, especially through the inventions provided by value estimate software. Building estimating software has unquestionably altered how experts conduct business and achieve their goals. It provides a streamlined process that gives forward-thinking companies a competitive advantage. Construction estimating software packages have become increasingly user-friendly since their introduction to the market, allowing manufacturing professionals to select task-specific requests and then personally tailored operating systems to generate projections. By reclaiming time, people come to realize that they are also reclaiming vital resources, as well as enjoying the convenience of this cutting-edge, task-specific solution [42].

2.9 RISK ELIMINATION IN CONSTRUCTION

A risk factor is a trait, ascribe, or element that increases the likelihood of harm and may alter the desired outcome. 12. Rule out 13 as a possible problem that could affect project objects. Furthermore, as a future circumstance that will have a negative impact on for at least one of the scheme's objectives with an incidence greater rate than 0percent but less over 100% [43].

Building project projected costs that do not account for risk variables jeopardize a firm's capacity to complete a job. As a result, the study's motivation has stayed the identifier of factors that are associated with program goal achievement. The study clearly designated and made a priority risk factor encountered by building service providers during the preliminary cost stage. The subject of the study has been chosen based on the concept presented in having to cut 14 of the connection between risk factors, hazard outcomes, and structural practices[44].

2.9.1 Strategies for Risk Factor

Health risk mitigation in pricing guesstimates were optional. 18. One of the preferred mitigations is peril identification. Those certain strategies include identifying significant project key risks in previous cost of the project, identifying nonentities during in the estimation step who did turn out to be margin mass murderers, and using this data to estimate future costs. 19. As presented in Figure (2.2), using risk management strategies and process improvement as part of a risk-mitigation strategy 20. Risk avoidance is also dependent on the company's awareness of external setting prerequisites during cost estimation and successive forethought of external factors such as regulatory expert prerequisites. also discusses risk-averse tactics employed during the bidding process. Avoidance or decreasing a bid open invite have also been mentioned as potential mitigation strategies when a risk is deemed to be above one's tolerance level 23. Post whenever possible, seeking specific data to reduce risk, enticing health insurance, and, only at extreme, all of the above are other methods [45].

Main risk analysis techniques		Zones																			
		mA	mB	mC	mD	mE	MA	MB	MC	MD	ME	m1	m2	m3	m4	m5	M1	M2	M3	M4	M5
qualitative techniques	Probability and impact description	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	Assumptions analysis	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	Check lists	⊗	⊗	⊗	⊗	⊗	●	●	●	●	●	⊗	⊗	⊗	⊗	⊗	●	●	●	●	●
	Probability-impact tables	○	○	●	●	●	○	●	●	●	●	○	○	●	●	●	○	●	●	●	●
	Data precision ranking	○	○	○	○	○	○	○	○	●	●	○	○	○	●	●	○	○	●	●	●
	Flowcharts			○	○	○		○	○	○	○			○	○	○		○	○	○	○
	Influence diagrams			○	○	○		○	○	○	○			○	○	○		○	○	○	○
	Cause-and-effect diagrams				○	○			○	○	○				○	○			○	○	○
	Event and fault trees				⊗	⊗				○	○				⊗	⊗				○	○
quantitative techniques	Sensitivity analysis	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	Probabilistic sums		○	○	○	○	○	○	●	●	●			○	○	○		○	○	●	●
	Monte Carlo and LHC simulation			⊗	⊗	⊗	○	○	●	●	●				⊗	⊗			○	●	●
	Probabilistic influence diagrams			⊗	⊗	⊗	○	○	●	●	●				⊗	⊗			○	●	●
	Expected value tables			○	○	○	○	○	○	○	○				○	○			○	○	○
	Decision trees				⊗	⊗				○	○					⊗				○	○
	Event and fault trees				⊗	⊗				○	○					⊗				○	○
	Multicriteria DMSM (AHP, etc.)				⊗	⊗				○	○					⊗				○	○
	Fuzzy logic										⊗										⊗
	Processes simulation										⊗										⊗
	Systems dynamics										⊗										⊗

Legend: ● normal / most frequent use ○ possible use for specific purpose / in specific circumstances
 ⊗ possible use preferably / necessarily with external help

Figure 2.2: Sample recommendations about use of risk analysis techniques [45].

2.9.2 Risk-Related Concerns with Cost Estimating

The text accepts the classification of issues arising in cost estimating. Risk factors influencing pricing forecasting have indeed been identified. as making up economic risk factors, injury risk elements, and building risk factors Building health risks are hazards associated with the production, industrial equipment, or labor in the functioning of the economy. This type of risk may be associated with plant or equipment accessibility, as well as hardware suitability, operator talent, and plant or equipment failure. Labor could include, for example, the accessibility of trained and skilled personnel, a strike, managerial skills, physical accessibility, as well as supplier insolvency [46].

Among the alleged construction risk variables are Physical peril Variables in cost analysis are physiological aspects of the project that may necessitate changes or remunerations to the construction project. Among them are design changes, poor detailing, undesirable weather, accidents, and material theft. Financial risk factors included the stability of a money flow, fluctuations, and inflation in the price of merchandise and materials. The following risk factors have been associated with the estimator's risk factors: the nature of the contest, the contract timeframe, the correctness of the plans and specifications, the completeness of a project scope definition, the foreseeability of changes throughout material and design, and the current workload, errors in judgment, the accessibility of data from previous works, and experience in particular projects [47].

2.10 LITERATURE SURVEY

The research discusses the time prediction models that are presented in the paper and thus are currently one of the most reliable forecasting models (Figure 2.3). The information were only subjected to the a conservative multiple linear regression based on the well-established "time cost" model before constructing and applying a statistical model for the same data. The scheme timeline is a critical component of the agreement in this study, according to each building agreement. This same experience demonstrates that the discrepancy between the contracted or rather actual construction phase is a major topical issue. A Provision Tunable is a relatively new modeling technique that has clearly proven its ability to generate predictive

results for a broad range of problems. It is common for build time to be set arbitrarily. Artifacts constructed between 1998 and 2011 as portion of Kosovo and Herzegovina's partnership were used in the analysis to predict this same building time to use the (Back Propagation Method). The fluidly founded designs seem to be purely structured and do not accurately represent the actual functionality of this same contracting company. Using Bromilow's "time price" perfect, a sequences reintroduction model was applied to the information for up to 80 objects. When the same data was subjected to a support vector algorithm, the prediction accuracy improved significantly. The results show that based predicting the future was significantly more accurate [48].

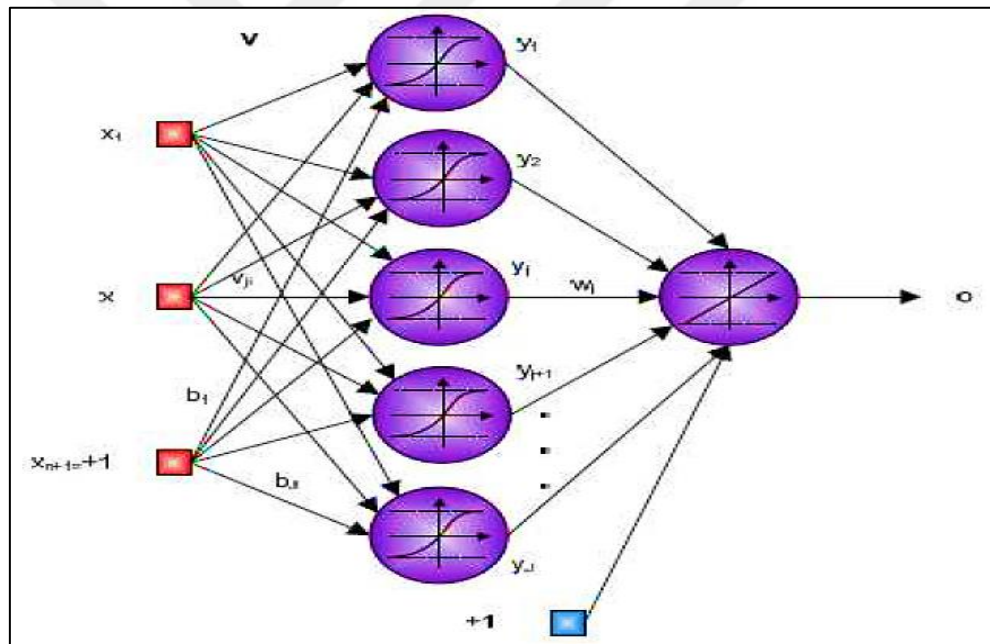


Figure 2.3: General model of SVM [48].

The research explains that the early and precise estimation of construction costs is a critical component of building construction schemes. The 98 percent coefficient of determination, as well as the lowest error criteria, spotlighted the traditional connection between the actual construction cost as well as the predicted expense. The goal of this research is to develop a forecast model for building project costs in India using vector support process analysis. Replete 80 data points of constructing new strategies from the Mumbai region of India were

acquired for the formation of the cost-predictive perfect. This research helps the Indian construction sector by providing funders with a generalized understanding of a project's total prediction. The linear, Function, linear function, and sigmoid kernels are used to construct the SVM model. The results of the created E RBF seed mechanism this model show that it outperforms the other models. [49].

According to the study, one of the major issues to sustainability practices is cost forecasting in the earlier start phases of construction. A hybrid approach combining the technic and the Bromilow time frame model (treatment regimen prototype) was used in this study to predict the target variable, true construction cost of roadways, from the available variables: contractual building cost, contracted construction time, as well as real building time and expense. 5 hybrid models have been developed for comparison: Bromilow is used in conjunction with regression analysis, radial basis function connection, multi - layer perceptron, and overall reversion neural network. According to the findings of the study, neither approach is the most effective in all circumstances. As a result, the research has been focused on hybrid modelling techniques, which is a combination of several methodologies. Preceding research has concentrated on process-based, then data-driven, model growth techniques including such regression model, vector machines, neural networks, and the like. Brimelow achieved the highest level of correctness, with a mean fraction mistake of 2%[50].

The study explains that for the sparse sample data and multidimensional non - linear feature of building company expense, Trials with Jiangsu Province cover project data show improved prediction accuracy when compared to other models, making it a useful technique for scheme cost forecasting. All applicant topographies are first ranked by association with the dependent mutable before constructing the construction cost forecast model of the smallest square support vector mechanism. a new hybrid prediction perfect combing genetic interpolation method after which small sample learning perfect based on least quadrangles support vector algorithms is proposed. [51].

According to the study, construction projects that aren't moving struggle to complete their work within the budgeted deadlines. a set of software for machine learning and data mining

that was used to shape the model for forecasting time and price indices by debtor, the calm data were split into three sets: a 30% validation set, a 20% testing set, and a 70% exercise establish. This lesson drew on information gathered from 21 tunnel plans used in Kurdistan, Iraq. When addendums and variations are factored into the schemes, the problem becomes more complicated. The purpose of this work was to develop a fictitious intelligent model that would predict project time and pricing indices using the provision vector machine (SVM) technique. The input data consists of five variables: contract value, contract duration, number of change orders, conflicts, and firm categorization. The results show that both the qualified data and ploys with input variables accessible for the entire range of training input data effectively forecasted the price index. The absolute percentage mean error as well as average for the cost index prediction were determined to be 13.9 and 86.1 percent, in both [52].

This training has espoused using an SVM model to assess hypothetical pricing estimates after study assessed the relevance and possibilities of SVM in construction regions. Just the conventional classifier examination framework was used in this study to investigate the future SVM method for assessing conceptual cost approximations. For every model's sixfold pass, 62 data values from general service providers in Korea were used. Furthermore, the SVM assessment model can assist clients in determining whether a second accurate estimate is required in the early stages of a project and evaluating the quality of an anticipated pricing. This method was used to assess the precision of conceptual cost estimates in regard to the error rate range. In order to assess the potential application and possibilities of the SVM model, the study assessed two different models, namely the model and also the classifier analysis model. The results showed that the SVM model evaluated conceptual price estimates slightly more accurately than the discriminant analysis model. This suggests that it has possibilities and relevance in the construction industry [53].

According to the study, the existing scheme costing method necessitates a large prediction nonconformity, a large data scale, and little understanding. According to the scheme function test results, the average forecast variance for the planned system is 4.11 percent, while the regular forecast variance for the cost predictive model is 3.05 percent. The switch core employs and includes a 4G transceiver in the game's hardware part to study engineering work

data with the assistance of hardware. The software portion recognizes the process flow cost prediction index system for the construction project. The main component method is then used to reduce the index, and the atom clustering optimization algorithm is used to improve the support vector mechanism (Figure 2.4). In order to improve the forecast precision of a entire procedure construction costs system, this study proposes the whole process system cost predictive model built on updated support course machine [54].

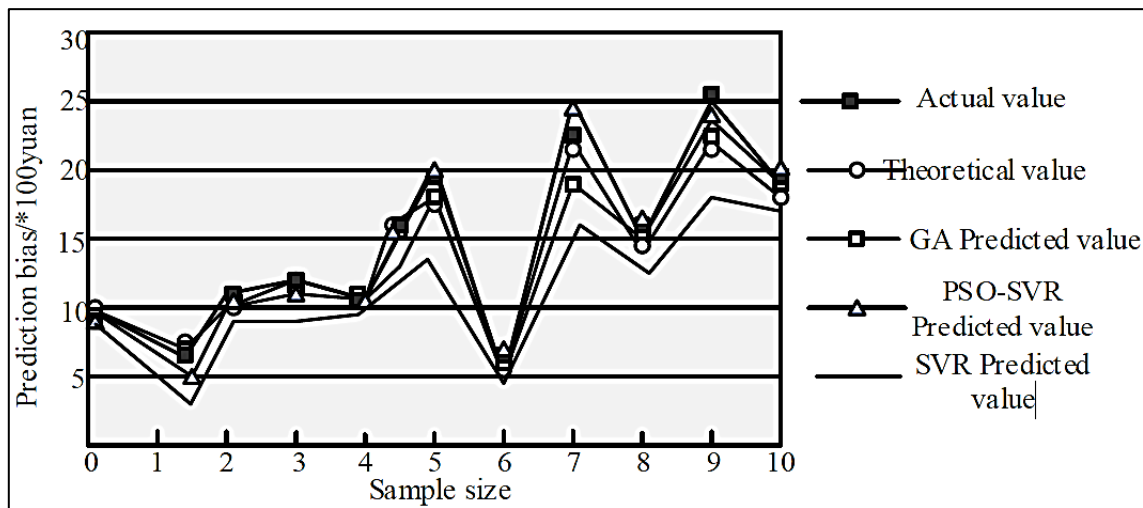


Figure 2.4: Comparison of the deviation between the predicted and actual values of construction cost of the whole process of the system [54].

According to the study, the project validity analysis is heavily reliant on modeling approaches approximation. The impact components of the cost estimate have been identified through a review of the systematic review and expert interviews. Case studies show that can assist planners in estimating the cost of a building project in a professional and concise way. In a relatively short amount of time, the algorithms provide such a satisfied accurate solution to a curved optimization problem. The construction modeling approaches estimation model is developed to assist owners and planners in forecasting project construction costs. The computation time is less than 5 minutes based on the training results, and the average validation loss is less than 10%. The error for a project's conceptual cost estimate is resolved during the planning and conceptual project phase. The cost of construction projects is used as a learning tool. The estimator's experience is used to determine repetition. However, as a

consequence of the inaccurate projected cost, planning and cost control are badly planned and carried out. Vector Support Machinery and equipment, an artificial intelligence technique, is used to approximate building costs [55].

According to the study, predicting building costs and minimizing time risk are critical aspects of management decisions. As a result, our publication has presented analysis and considerate papers that have suggested cost assessment using mechanism learning methods over the last 30 years. Machine learning algorithms require a large enough dataset to estimate and forecast project costs. The recommendations for education are primarily focused on gathering actual research from Science Connect and Google Scholarly journals. Although the measureable strategy is investigated, it reflects the mechanism learning strategies. For the quantitative approach, the copies were divided into three categories: statistics, equivalents, as well as analytical models. The replicas were then analyzed based on their features. The second section focuses on the proposals' analysis. There are two techniques for cost analysis to consider: qualitative and quantitative. The most important outcome of this research is the revelation of various analytics techniques, followed by machine learning algorithms used to predict the approximate construction project costs and related projects and assist in the identification of the best appropriate applied techniques. In accordance with this, publications have continued to be thoroughly examined based on the application ground, method used, methods put in place, journals in which they have been published, and year of publication. highway, public, roadway, construction. The main contribution of this manuscript is its thorough examination of machine learning techniques and the application of an assessment methodology in cost estimation based on direct and indirect costs of construction projects, which are divided into two parts. Liquid structures, street tunnels, railroads, hydropower, power vegetable, and hydroelectric dams are the requested project price assessment areas of interest. [12].

According to the study, the bridge's construction plan being completed on time and within budget is one of the key components of a project's success. The ability to accurately predict bridge construction costs suitable for early project phases influenced the final roster of the best possible solutions. The overall testing metrics again for final perfect, also known as the root mean square mistake was 2, the connection between actual bond construction costs and great

model price predictions was 0.980, and the mean total error percentage was 11. The study provides findings on the development of cost prediction using machine learning, namely that the support vector machines. method, with basic data and bridge characteristics open network in the early stages of projects as input. This requirement is more likely to be met if projected costs, particularly those made earlier than usual in a project, are accurate and connected to a final cost. A variety of quality of decision-making replicates for concluded Polish bridge infrastructure projects were investigated using data calm. After completing the machine learning as well as set rules and meeting the criteria for satisfactory information generalization capability and performance, five replicas were pre-selected. The study resulted in the development and application of a novel methodology that was able to provide accurate early estimates of bridge construction costs [56].

The study's goal is to develop construction price and action success prediction models using collected data from 92 building projects in order to educate the building industry in the model - based results demonstrated that, for the sample projects examined, the planning phase state can be successfully applied to forecast project results utilizing artificial intelligence modeling approaches. The research findings provide conclusive evidence that, in the case of the sample projects, requirements to meet results in better project outcomes. False intelligence model - based methodologies are also more suitable for non-linear sample data once compared to traditional statistical reversions. Taiwan about early planning repetition and its relationship to final project consequences. The Scheme Definition Rating Index was employed as the survey instrument in this study. Artificial Neural collaborative model's startup combining as well as adaptive boosting classifiers are formed and verified to be as nutritious as Support Vector Machines classifiers using data from the 92 sample strategies. The model produces the best prediction results, with an overall correctness of 90% when predicting project pricing success. When predicting scheme schedule achievement, the adaptive growing model, which is now state of the art, produces the best prediction results with an overall accuracy of 60[57].

According to the study, numerous factors influence the final cost of the project for building projects. The Guesstimate at Calculation is useful for estimating project costs because it takes into account risks as well as likely performance of projects. If managements' credible new fad

predictions enable for an improves the speed of project costs, they should take appropriate preventative actions to address near term issues. Estimate At Completion (EAC) assists project managers in identifying potential but unknown issues and implementing response strategies (Figure 2.5). This work created an evolution that really is ideal for generating project price estimates that are noticeably more reliable than estimators made using currently the most widely formulae. The discrepancy between guesstimate and practical values was investigated using the estimation, project cost effect index values, and scheme cost diagrams to assist project managers in more successfully switching cost of the project. The industrialized learning model combined the rapid disordered evolutionary algorithms and the Endorse Course Machine, two binary artificially intelligent techniques, to produce the Differential evolution Support Vector Machine Implicit Assumption Model. Previously, was used to determine final cost of the project for completed instances. Practical applications that proved strong performance for learning algorithms allowed the learning's to be validated [58].

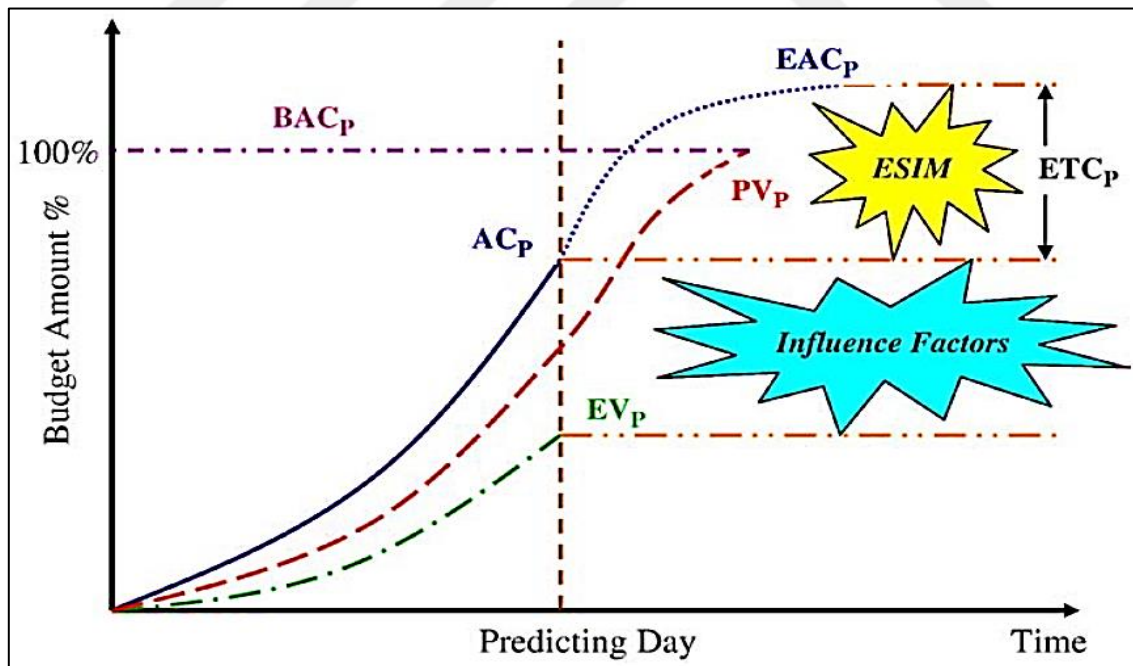


Figure 2.5: EAC prediction model [58].

The research looked into risk factors inside the cost analysis of framework building projects. The research has discovered too many possible risks that stem from risk issues. The results

indicate the risk factors that estimators perceive to be the most dangerous to cost forecasts. It is now suggested by schooling for not only service providers to be vigilant in risk mitigation problems, but also for clients to take this cleverness as they are sure to regularly suffer once inexact cost estimates have been dedicated to a project. Project delays, price overruns, and performance disappointments are examples of hazards that have been identified as working against the achievement of project goals. The investigation looked into four types of risk factors: building, physiological, monetary, and estimator's risk issues. Overall, respondents rate all four risk factor categories as having a moderate to high influence on project presentation. An investigation was conducted into the risk posed by danger variables as regarded by building contractors. The data was gathered through the use of questionnaires, with a total of 61 surveys distributed to structure construction companies[46].

This paper's dedication has a particular impact on the early stages of BIM-based project estimation. Estimated costs evolve in tandem with project lifespan stages; contextualization, conceptual design, implementation, and facility management, depending on information available and project requirements. Despite the slow start, Building Info Modeling has effectively solved a number of issues previously associated with traditional methods in the AEC, such as poor communication, the pervasiveness of information islands, and recurrent reworks. This hypothesis proposes that faking conventional costing estimation issues variables can improve the accuracy of BIM-based estimation as additional efficient, procedure of traditional price estimation techniques. These same results indicate that many factors influence cost estimates, including project documentation and characteristics, project side, clients, votive matters, and other external influences. The importance of price estimate accuracy is critical in generating project tenders and, ultimately, budget organization. Cost estimating has long been recognized as an important component of construction projects. As a result, it is possible that BIM can be used to address specific cost estimation deficiencies. The motivation for using BIM models for precise cost estimation would be to align budgeted and actual costs. This daily paper investigates the factors that may lead to the more accurate estimated costs for construction industry through job feedback and preliminary skilled interviews [59].

The schooling demonstrated Construction schemes are becoming more complex as their scales become more sophisticated. For information research, Comparative Global Status was used. Seventy variables have been investigated in total, and the best five most important were chosen by this evaluation based on the median view of defendants. These significant issues are as follows:

Content value/accessibility/basis/quality/introductions, Encounter and aptitude of the consultant, Variability in the country's currency, as well as the client's financial situation Spearman's robust correlation coefficients investigation was led by the assistance of SPSS 20 version for just a testing level of links among respondents just on placement of the factors influencing the accuracy of cost estimation. Along these lines, finishing projects with confidential planned cost limits is becoming increasingly difficult. These flaws were raised as a common challenge in Oromia public structure construction projects. The goal of this study was to evaluate issues affecting the accuracy of cost estimation in community projects in the future. Information was gathered using both qualitative and quantitative methods. Spearman's rank correlation results were 0.9 between Clients and Advisors, 0.7 between Clients and Servicers, and 0.7 between Consultants and Contractors. The result shows that the degree of the rank affiliations was a high optimistic number, implying that there is a positive relationship between them on the leaderboard of issues affecting the accuracy of calculations in society construction projects for buildings in west Regional state [60].

2.11 SUMMARY OF PREVIOUS STUDIES

In order to investigate the possibilities of use skill in price estimation. Making a cost estimate after receiving the over project is labor-intensive work, owing primarily to the takeoff. In the case of the SVM model, the budget should be present during each phase of the project to determine how objects and aspects are to be labeled and modelled if slight automation of the cost-estimating procedure is required. It should also offer suggestions for how to simplify the model's elements and how to choose a validation object to couple with the motioned model. A literature review of data about price - estimating and departure in SVM has stayed done for that intent, as well as a team scheme designed to showcase the main subject's cost-estimators

then developers can confront. Regular communication between designers and methodologies allows a used model to be shaped for further processing in various SVM tools. The requirement for constant communication allows for better conveying information. Even so, during the cost approximation phase, the price estimator's labor input should be marginal because the departure and parts of the price estimate can be completed automatically and quasi.

2.12 CURRENT STUDY CONTRIBUTION

In order to evaluate the conceptual cost of building projects and to generalize the input-output connection for brand-new input data, a novel intelligent model based on cross-validation and support vector machine approaches was suggested in this research. The study collects the related information that can be adopted to build updated cost estimation system that can be improve the management of construction project based on the support machine vector technique. The study pathway included the identification and the evaluation of the influential factors for the construction process. The study arranged the analytical steps in the outline to develop a machine learning-based regression mode by using the support vector machine (SVM) method. The study showed the results in the way of supporting early estimates of total construction costs of construction building.

3. METHODOLOGY AND MODEL BUILT

3.1 GENERAL

Both the original cost of capital investment and the ongoing costs of operation and maintenance are included in a facility's total cost to the owner after it has been constructed. The costs associated with each of these primary categories are broken down into a variety of subcategories. The scale of each of these cost components is determined by a variety of factors, including the nature of the project, its size and location, and the management organization. Other factors also come into play. The goal of the owner is to achieve a level of overall project cost that is as low as possible while still meeting the requirements of its investment goals. Although the cost of construction may be the single largest component of the capital cost, it is essential for design professionals and construction managers to understand that although other cost components are not insignificant, the construction cost may be the single largest component of the capital cost. For instance, the cost of acquiring land is a significant portion of the overall expenditure for building construction in high-density urban areas. Furthermore, the cost of construction financing can approach the same magnitude as the overall construction cost in large-scale projects such as the building of nuclear power plants. It is equally vital, from the point of view of the owner, to estimate the relevant costs of operation and maintenance for each alternative that is being considered for a proposed facility in order to conduct a life cycle cost analysis. The large amounts of money that need to be spent on facility maintenance are a stark reminder that, in the past, the implications of operation and maintenance cost were not taken into full consideration during the design stage. This is especially true for infrastructure that is owned by the public sector. There is typically some sort of buffer or contingency fund included in construction budgets to account for unforeseen expenses that might arise throughout the project. This amount of the construction contingency can be included in each individual cost item, or it can be included in a single category of the construction contingency. The amount of the contingency fund is determined by prior construction experience as well as the degree of difficulty that is anticipated for a specific building project. Near the completion of the construction project, any contingent

funds that have not been spent on the project can be returned to the owner or used to add more components to the project.

According to the owner's requirements, the final bids are generally presented on the basis of either a flat sum or a unit price. A lump sum bid is the whole price that a contractor is willing to charge to finish building a facility in accordance with the exact plans and specifications. Putting in a bid based on unit pricing is done for projects where there is a great deal of uncertainty regarding the quantity of supplies, or the amount of labor required to complete certain essential tasks. In situations like these, the contractor is allowed to provide a list of unit prices for the specified tasks, and the final price that is used to determine which bidder submitted the lowest price is based on the lump sum price that is computed by multiplying the quoted unit price for each specified task by the quantity that corresponds to that task in the owner's estimates for quantities. On the other hand, the final sum that will be paid to the successful contractor will be determined by multiplying the actual amounts by the various unit values that were quoted. The practice of awarding building contracts to one or more pre-selected companies rather than holding competitive bidding processes is common among private owners. The flexibility of this kind of pricing arrangement is one of the primary reasons why negotiated contracts are used for construction projects, particularly those projects that are either extremely large and complex or projects that substantially duplicate previous facilities that the owner has sponsored. An owner may place a high value on the experience and honesty of a particular contractor, particularly if that contractor has a solid reputation or has previously completed successful projects for the owner. If it becomes necessary to meet a deadline for the completion of the project, the construction of a project may proceed without waiting for the completion of the detailed plans and specifications with a contractor that the owner can trust. This is possible if it becomes necessary to meet the deadline. However, the team working for the owner needs to have a significant amount of expertise and be highly skilled in order to evaluate contractor offers and monitor future performance.

3.2 CONSTRUCTION PRODUCTIVITY FACTORS

The construction business has always been thought of as an industry that is heavily dependent on human labor. The manufacturing that takes place in this region is characterized by its huge scale, open job sites, and substantial fragmentation throughout the process. As a result, the building sector has, for a very long time, been considered to be "extremely inefficient." Customers and those in charge of making decisions are quite concerned about the industry's performance as a result of the comparatively modest productivity increase it has had in comparison to other industries, such as the manufacturing industry. It has been determined that one of the most significant issues facing the building business is low productivity in the construction sector. According to the report that was put together by the CIDB Construction Productivity Task Force in 1992, the manufacturing sector of Singapore and the construction sectors of other developed countries were viewed as having higher levels of productivity than the construction sector in Singapore was perceived to have. In Singapore, the construction industry employs a disproportionately significant fraction of the nation's entire employee pool in comparison to the sector's contribution to the economy. This is mostly attributable to the labor-intensive nature of the business.

3.2.1 Labor Productivity

The significant construction planning should consider and track labor factors in the original work scope. This is necessary to accurately reflect all of the conditions that were used to estimate and fund the project. Additionally, this is necessary to eliminate or minimize the impact on productivity, which will directly affect the costs of construction. Alterations to the job scope that take into consideration the effects of labor should also be included as part of the sequencing and planning of any activity. Work planners can be assisted in the management and control of labor impacts by using technology such as Intergraph Smart Plant Construction. This type of technology gives users the option to add and alter labor factors specific to their project. Users are also given the option to view and animate work packages, and they are given the flexibility to alter the order in which work packages are executed in order to minimize or lessen the need for labor factoring. In addition, Smart Plant Construction has the ability to generate documentation for work packages, which may be used to either support or

refute construction claims linked with labor factoring. The level of productivity achieved is dependent on a number of interconnected factors.

i. Work Scheduling Method

The construction industry is notoriously inefficient because of the numerous jobs that plague projects. Working overtime has been shown to reduce productivity in previous studies. Fatigue, increased absenteeism, low morale, ineffective supervision, sloppy work resulting in more rework, and more accidents are often cited as causes. Compressing the total time frame for a later activity is a common approach to make up for interruptions and finish the allotted assignment on time when there are delays early in the project. Professional schedulers know that using float in the overall timetable can help them compress the calendar without having to speed up individual work tasks. However, many projects fail to completely load their schedules with resources. Therefore, the project may still end on time without any operations needing to be shortened if the schedule is correctly revised to reflect the delays. In order to accomplish the remaining work on time, contractors may need to put in more hours than originally planned if their schedules are compressed. When schedule compression is combined with overtime, it can lead to significant losses in productivity because of insufficient resources to handle the influx of workers, which makes it harder to plan and coordinate the work at hand and reduces the availability of skilled workers.

ii. Number of Supervisors

Modifications to plans, blueprints, and blueprint specifications are commonplace on building sites. If there are mistakes or ambiguities in the drawings or specifications, workers on the ground will be less productive. There is a risk that the task at hand will be slowed down or even abandoned until more direction is given. When switching tasks, productivity drops by 30%. In order to move forward, it is necessary for the supervisor to conduct inspections of the work. The contractor's ability to cast concrete, for instance, would be impeded by the need for a formwork and steel work inspection before any work could be done. If a project is not finished according to the requirements and drawings, a supervisor may request that it be redone. When supervisors aren't present, work pauses completely on tasks like casting

concrete and backfilling; this, in turn, delays inspection of finished work and the subsequent beginning of new tasks.

iii. Workers Experience

There is a connection between a project's price tag and the expertise of its staff. Employees' lack of ability to put their expertise to use in managing the project is one of the leading causes of its failure. Working efficiently and effectively throughout the project life cycle is directly related to a project's ultimate success. There should be an enough number of skilled workers hired on the construction projects for them to succeed. Productivity may suffer if a contractor is forced to execute a task that normally requires expert workers with less-qualified employees. Since workers normally won't be able to accomplish the same production rate with fewer resources and with a different crew member, the absence of any crew member may impair the crew's production rate. Disagreements regarding who is responsible for what and how far each worker can go in their work are the result of misunderstandings among workers, which in turn causes a high rate of errors and a drop in output. Due to a reduction in speed, agility, and strength with age, labor productivity is significantly impacted by low wages and an aging workforce.

iv. Change Task Type

Determining the critical route requires a thorough understanding of the important task milestones, which can be achieved by clearly defining the tasks at hand. This is so because these protocols serve as the basis for the rest of the project management framework. The project team will be unable to successfully plan ahead unless everyone has a clear understanding of the tasks that must be completed along the way. It's not enough to simply list the tasks; we also need to define what goes into each activity and include any associated subtasks. The most effective strategy for achieving this goal is to collaborate with influential people from every division of the building industry. General project managers will have a wide breadth of understanding but little depth of competence. However, managers and supervisors in specialized areas have in-depth familiarity with the core activities in their respective fields and how they affect the project. They are also able to see how the

accomplishment of one activity or area depends on the achievement of another, and vice versa. identification and characterization of tasks shouldn't be restricted to just the physical parts of building. Processes should factor in evaluations, audits, and other forms of paperwork. The time it takes to obtain necessary permits is a major time sink for building endeavors. in order to consider these factors equally important in advancing the project along the critical path.

The time gap between when a task was supposed to begin and when it really began and how long it took is an example of task variation. The level of productivity achieved on a construction project is affected by the degree of work variety. Large construction projects involve a wide variety of interconnected activities. One task's variation in start time and/or duration might have unintended consequences for other activities further down the line, leading to schedule interruptions and/or lower productivity. Understanding the underlying causes of the variation is challenging because of the construction process's complexity and the large number of people involved, each with their own area of responsibility. Workers, foremen, and project managers were polled across the country to determine the most common factors contributing to beginning time and task duration variation, as well as the degree of each.

3.2.2 Equipment Productivity

Modern construction sites rely heavily on a number of resources, and construction equipment is among them. The proper choice of construction equipment is crucial to the success of many building projects. Managers of machinery frequently face the necessity of making tough monetary choices concerning the equipment under their purview. Their responsibilities consist of fixing, rebuilding, and maintaining things. The failure to properly supervise equipment accounts for roughly 30–40% of all construction cost overruns. According to the frequency analysis method, the most common cause of project cost overruns was the effective construction strategy of equipment maintenance. The criteria are categorized, and the impact they have on equipment choice is quantified. Management equipment selection framework development. The research could have benefited from the use of cutting-edge tools and techniques. Here, the model calculates the minimum present value of total expenses based on

the future life cycle costs of the equipment using the arithmetic and geometric gradient method. Choosing the right construction machinery for the job site is crucial to finishing on schedule and within budget. One of the most important considerations in managing construction machinery is cost effectiveness. Defensive maintenance is another crucial aspect of efficient management of construction equipment that can save money, time, and frustration. Everything from a screwdriver to a truck and a crane is considered equipment since it can be moved easily. Complicating matters further, the sophistication of modern building projects makes it more challenging to evaluate and properly select among available equipment options. Equipment managers use their expertise to make decisions on the day-to-day management of equipment operations, as well as strategic activities like the purchase of new equipment. Thus, equipment managers face a significant challenge in their charge to ensure that all pieces of machinery are put to their best possible use. To get the most out of such a massive investment, construction machinery should always be running smoothly. High rates of productivity should be realized both during operations and during planned repairs and maintenance. The main effective sub factors of this case are:

i. Equipment Availability

In construction, productivity of tools and machinery can be tracked and enhanced in real time. Because of this boost in productivity, production rates, profits, and downtime can all improve. Equipment rental, purchase, and operation are all part of managing a construction site. Therefore, productive equipment standards benefit from efficient and effective methods. Some tasks call for specialized machinery. Both undersized and oversize equipment increase the time and money needed to complete the operation. Select the right kind and amount of tools, equipment, and gear to maximize your operators' productivity and minimize delays. If you do it right, renting equipment can be just as efficient. Make sure the vendor you're renting from is an official distributor for the brand and follows all standard operating procedures and regulations for equipment maintenance before signing a rental agreement. Equipment failure or malfunction is a real risk when hiring machinery that not everyone has the skills to fix. Large-scale building projects can also fail due to downtime and poor quality, which drives up operational expenses.

ii. Equipment Scheduling Efficiency

The effectiveness of a construction project's schedule directly affects the output of a project's machinery and tools. Construction machinery, like employees, is an invaluable resource that must be managed properly. Planners in the building industry must factor in times for service, inspection, maintenance, and handoffs. An increase in the project's hourly cost may result if any of these variables delay its completion. The manager's scheduling needs to be precise in order to maximize production. The final price tag might be affected by even a minor slip-up during building. Having a strategy in place for when and where each piece of equipment will be used is a huge time saver for project managers. Planning entails outlining the stages of the project and thinking about the resources and assets that will be required to reach the end result. This is when the scheduling of said equipment can prove useful. Important considerations for the site manager in scheduling used equipment include who will be in charge of each piece of machinery and for how long. The management can then make decisions based on this information, ensuring that a tool can be scheduled at the appropriate time and that no scheduling conflicts will arise. The management will be able to determine if it is more cost-effective to wait for the item to become available, or to rent or purchase a replacement tool, if effective scheduling is in place. Managers may confidently plan projects when they know all necessary equipment will be available thanks to the elimination of double booking and shortages made possible by tool scheduling solutions. The project manager may keep tabs on daily progress, make sure they have adequate time and resources to complete the project, and identify where the project is experiencing difficulties by making use of a project schedule.

iii. Maintenance Quality

Proactive and reactive elements both contribute to the efficiency of construction machinery. A simple justification can be given for why maintenance is a proactive aspect. For starters, it keeps machinery working better for longer. Heavy machinery requires regular servicing. Inspection, cleaning, and repair of hydraulics, engines, and other moving parts of heavy machinery constitute equipment maintenance. Preventive and reactive maintenance are the two primary modes of care for construction machinery. Scheduled oil changes, inspections for low tire pressure, and thorough cleaning are all examples of preventative maintenance

procedures. But when a machine breaks down or isn't functioning at peak efficiency, that's when "reactive maintenance" kicks in. As specialists determine the equipment's flaws, it could require more downtime and cost more than preventative maintenance. If a company takes care of its heavy machinery, it will see benefits across the board. In addition to the monetary cost, construction companies often see a drop in revenue when they are forced to respond reactively to breakdowns in their machinery. If a single asset is rendered inoperable for an extended period of time, it can quickly start off a chain reaction that leads to lost business, unhappy customers, and lower profits. When you put money into regular maintenance and preventative measures, the likelihood of this happening decreases. Maintaining and inspecting your equipment on a regular basis might help you spot problems before they disrupt your workday. A culture of appreciation for corporate equipment can be fostered by instructing workers to undertake routine checks of oil levels, gasoline levels, battery life, and tire/track conditions. Construction sites provide unique dangers due to the presence of heavy machinery. It's important to reduce danger by keeping these massive machineries in good functioning order.

iv. Suitability Of Equipment to Site Requirements

Construction projects in the modern day are highly mechanized, and this trend is only increasing. With construction becoming increasingly mechanized, worksite machinery and tools play an increasingly important role in maximizing output. When it comes to building something, having the correct tools for the job has always been essential. Common practice dictates that this can be made by comparing the duties at hand to the fleet's available equipment. Equipment capacity, cost, and productivity are all taken into account. However, the new concept of sustainability in building has put an emphasis on efficiency, the environment, economics, and people. The tools and machinery used in building a structure can vary depending on the nature of the job. Equipment and machinery utilization is often low to moderate on commercial projects. Machines were used extensively and extensively in industrial and heavy construction projects for tasks such as mass excavation, stabilizing, compacting, asphalt paving and finishing, pipelines, railroads, and many others. Earthwork, structural steel works, concrete, building, lifting, and positioning components are only some of the many prevalent uses for heavy construction equipment. In the realm of heavy construction,

projects can be classified as either horizontal or vertical. Earlier building styles necessitated extensive excavation and earthwork, but more lifting work than digging is characteristic of later building styles. To boost construction efficiency, particularly for infrastructure projects, heavy equipment plays an essential role. However, building companies need substantial investment funds to purchase them. As with other costs, it is a crucial consideration when budgeting for a building's construction. Purchasing major machinery accounts for 36% of the entire project cost and is fraught with uncertainty and risk, according to the available literature.

3.3 CASE STUDY OBSERVATION

Engineering drawings are used by engineers and other design professionals as a means of conveying conceptual ideas and technical details to one another. Engineering drawings use a technique called projection to depict a three-dimensional item on a two-dimensional sheet of paper or screen. Technical drawings like those used in engineering are one way of conveying information about a product. One common application of detail drawings is to outline the geometric specifications for fabricating a certain part. To fully specify even a simple part, it typically takes multiple drawings. A master drawing or assembly drawing serves as a connector between the individual drawings; it lists the drawing numbers of the subsequent detailed components, specifies the amounts and materials needed for building, and may even include 3D representations of the parts to aid in their identification. While largely visual in nature, they may also make use of acronyms and symbols for clarity, and further textual explanations may be included as appropriate. Creating engineering drawings, also known as technical drawings, usually involves showing several different angles of a component. Sometimes, scratch views of features are included to further explain the design. In most cases, only mandatory details will be presented. The most important details, including dimensions, are typically only stated once on a drawing to prevent confusion and duplication. Tolerances are provided for important dimensions that are necessary for the component to be built and to function properly. Based on the data provided in an engineering drawing, more precise manufacturing drawings can be created. The title block or information box of a drawing will often include the following: the name of the person who drew the drawing, the name of the

person who approved the drawing, the units of measurement used, the meaning of the views, the title of the drawing, and the drawing number.

3.3.1 Applying Revit Drawing

The building industry relies on Autodesk Revit, a building information modeling software product used by architects, landscape architects, structural engineers, MEP engineers, designers, and contractors. Charles River Program, established in 1997, rebranded as Revit Technology Corporation in 2000, and purchased by Autodesk in 2002; they created the initial software. Software users can create a 3D model of a building and all of its parts, annotate that model with 2D sketching tools, and then look up relevant building data in the model's associated database. Revit is a 4D BIM program that can be used to plan and monitor the entire building's lifecycle, from the initial design to the final tear-down. Building information modeling, or Revit, was developed to help architects and other building professionals create a parametric, three-dimensional model that includes both geometric and non-geometric design and construction information. Several competing programs offered a similar three-dimensional virtual building model with parameterized control of individual components, such as ArchiCAD and Reflex (parametric components). The model captures all relationships between components, views, and annotations so that a change to any element automatically propagates to keep the model consistent; this is in contrast to the traditional approach of using a programming language to create parametric components, which is what most other CAD programs require. The phrase "parametric building model" was used to describe how changes to parameters affected the entire building model and its documentation rather than simply its parts. The drawing process (Figure 3.1) for the present case study as in below:

The selected building with a dimension of (20m x 20m) was selected to be draw in Revit software

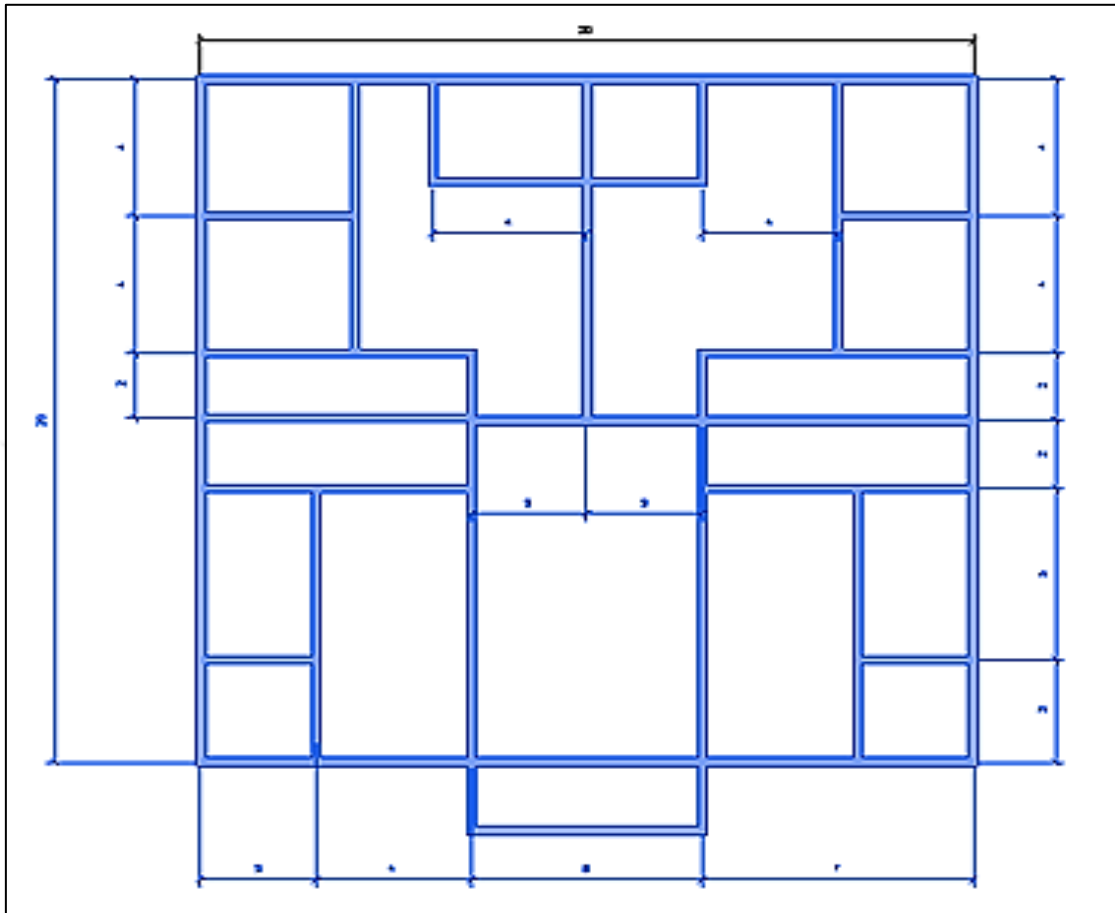


Figure 3.1: Walls with the dimensions of the case study building.

When applying the walls from architectural part of the software, the families of doors and windows will be used to apply them in the drawing and the building levels can be specified and monitored from the (Project Browser) as in Figure (3.2).

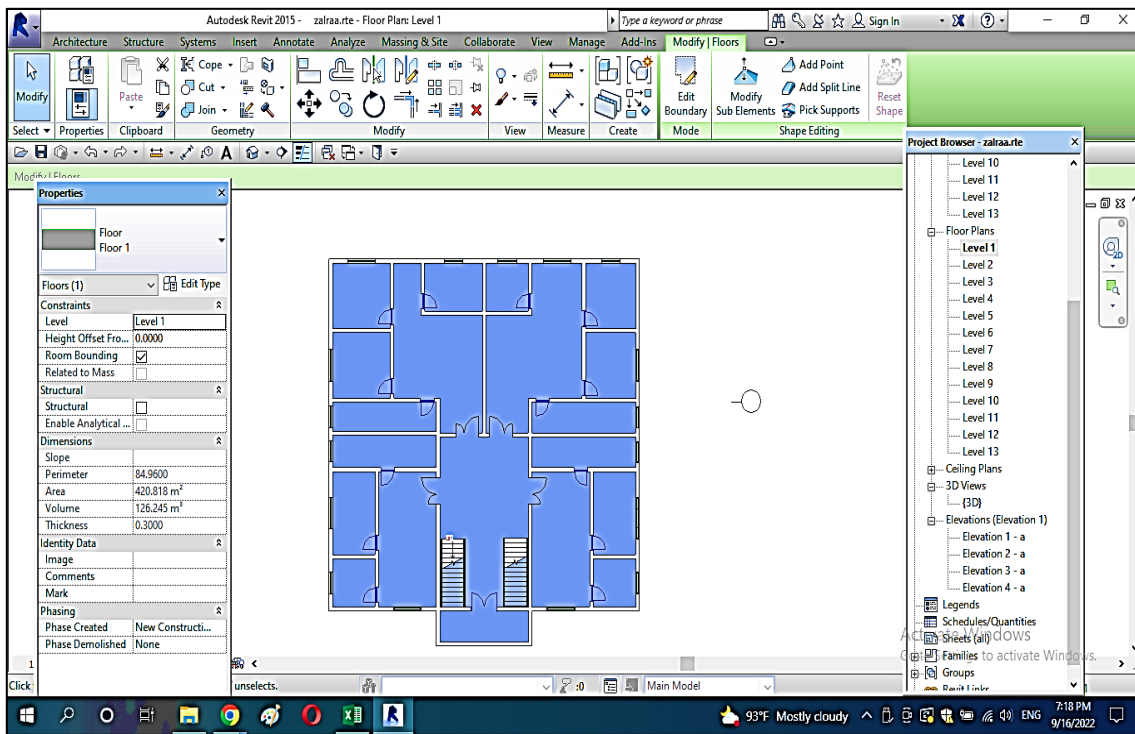


Figure 3.2: Applying the families of doors and windows.

When a wall was moved, for instance, the surrounding walls, floors, and roofs had to be updated, as well as the location and values of dimensions and notes, the floor areas given in schedules, the redrew section views, etc. Throughout its development, Revit was distinguished by its support for bidirectional associativity among components, views, and annotations. Revit is an abbreviation for "Revise Instantly" and was chosen to reflect the program's user-friendliness. Revit's core functionality is a parametric change propagation engine that uses context-driven parametric, a new technology that is more scalable than the variation and history-driven parametric often found in mechanical CAD programs. It can be seen from the properties that the specification of doors and windows can be monitored in the (Properties Viewer Message). The results of this step can be shown in 3D viewer as in Figures (3.3 and 3.4). all the necessary needs such as stairs will be added in this step.

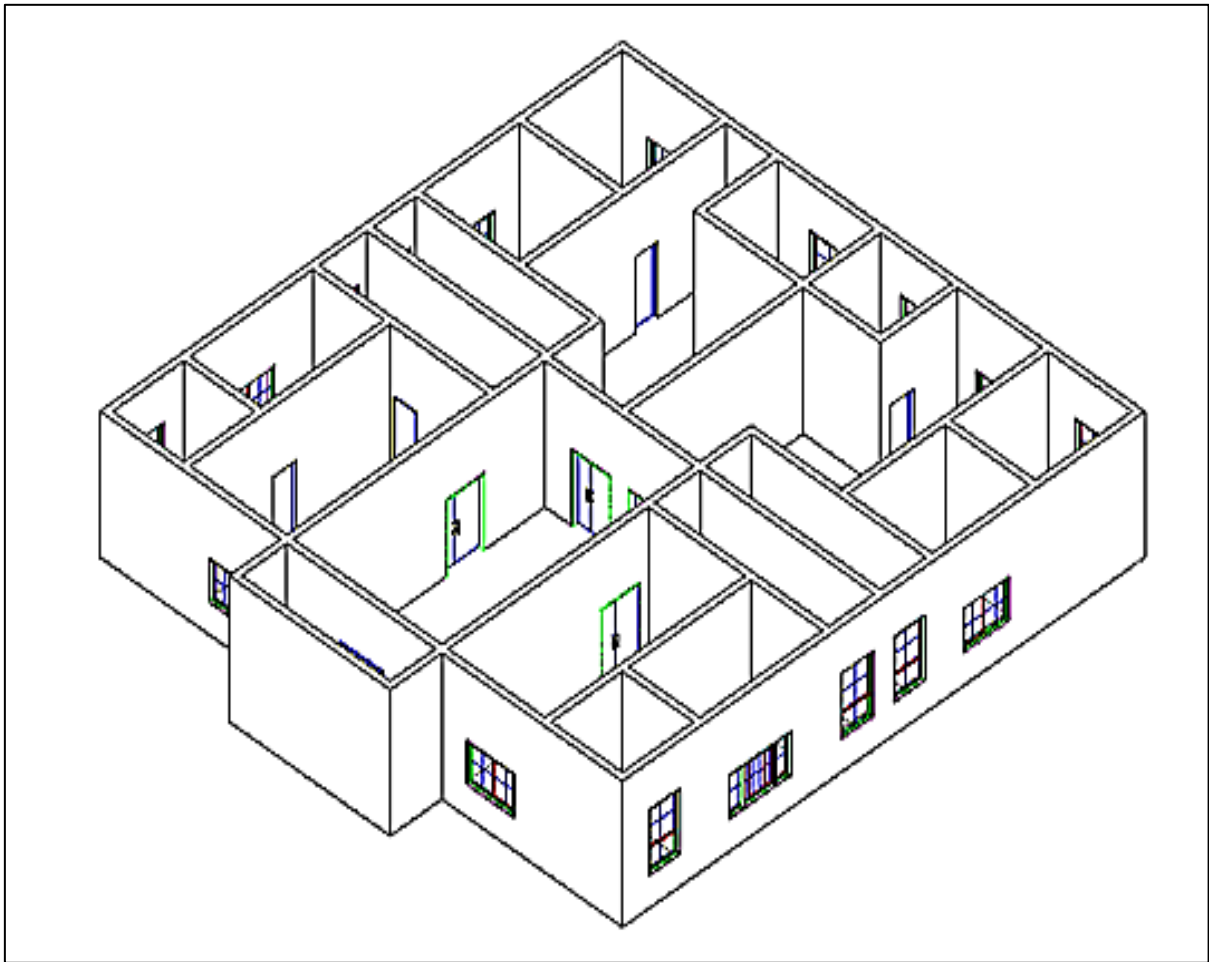


Figure 3.3: 3D of the first floor.

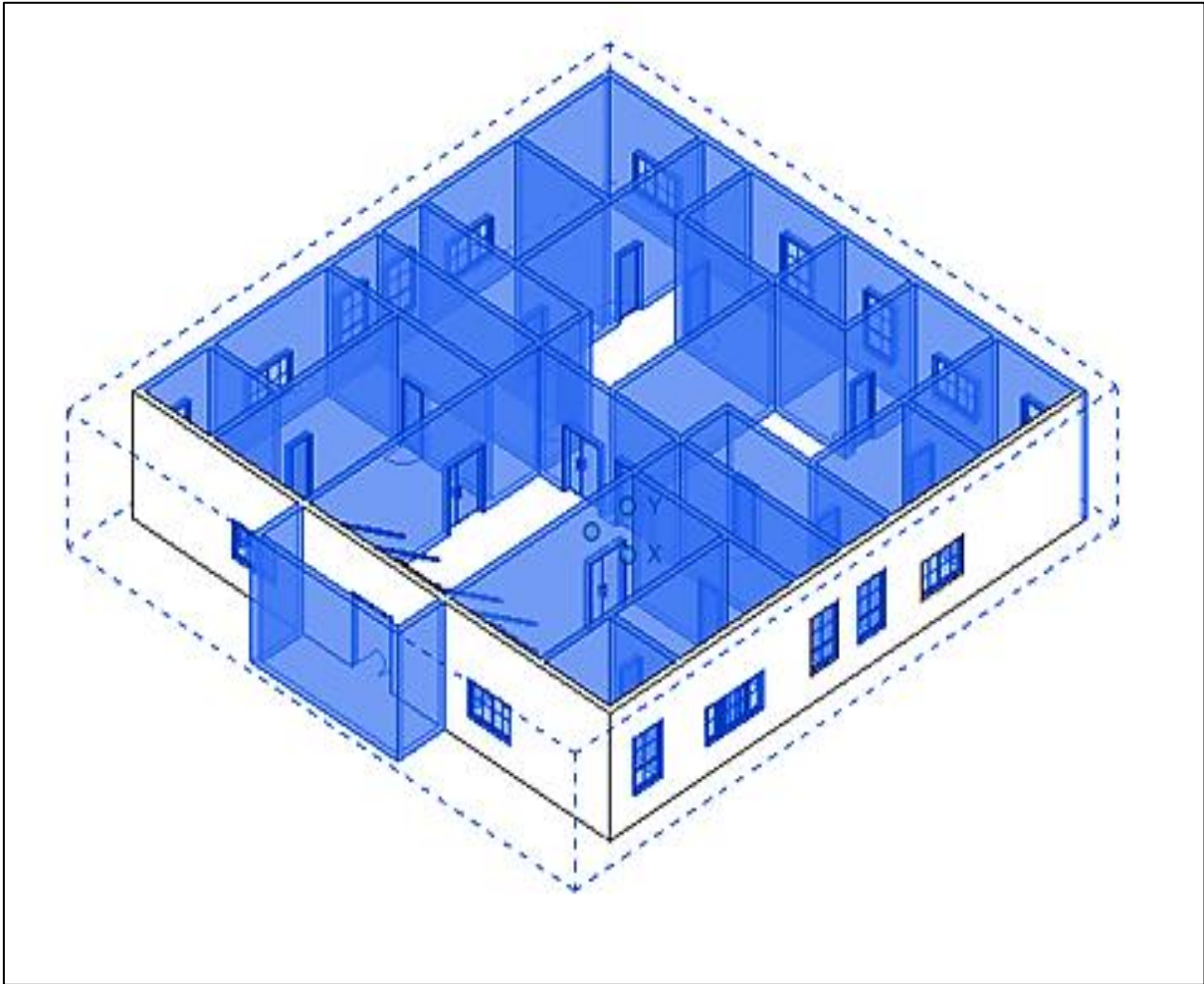


Figure 3.4: Assembly group of the first level of the building.

The next step is to build the similar floor components with the 10 levels as shown in Figure (3.5).

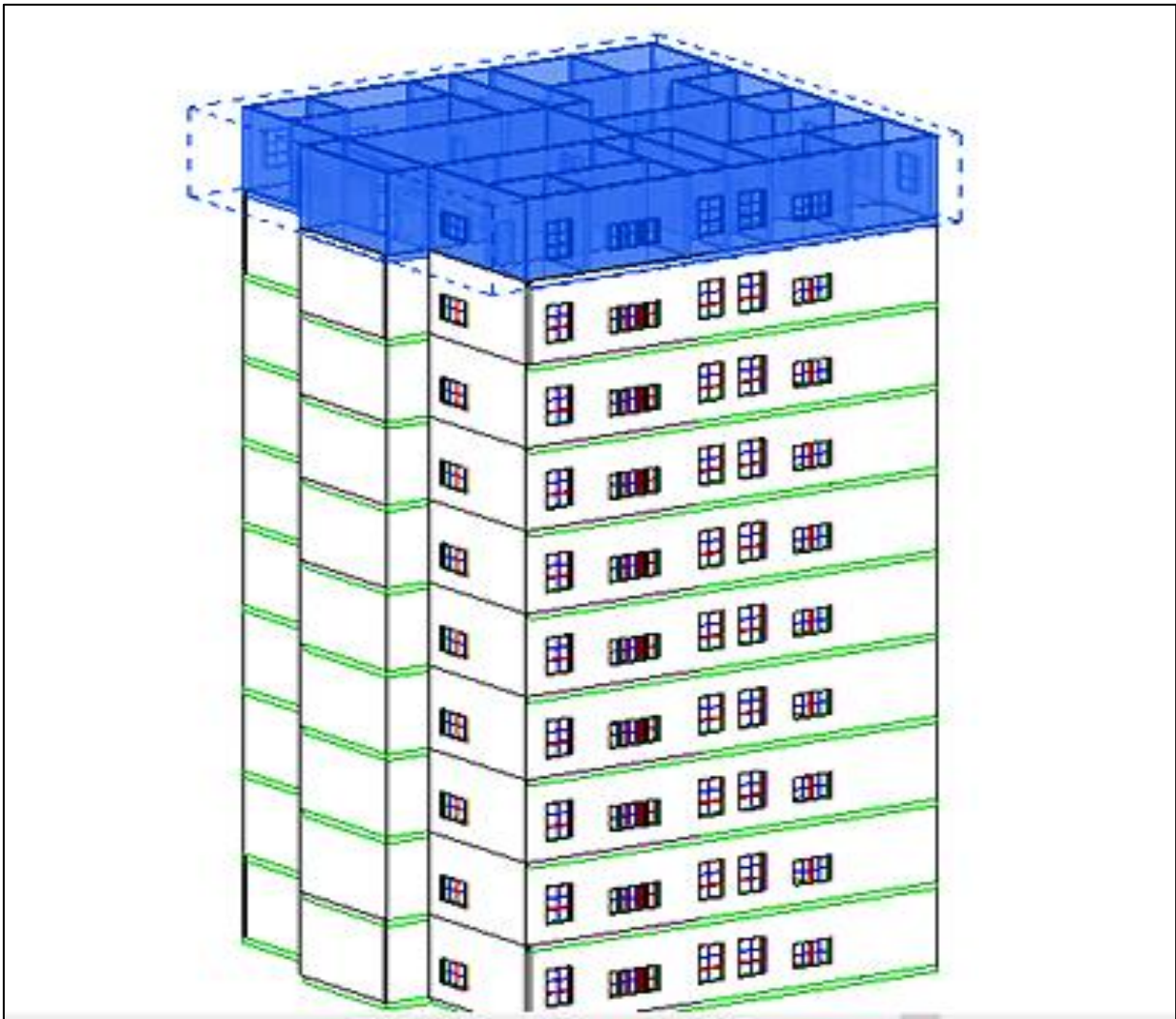


Figure 3.5: Applying building levels.

The Revit is able to modify individual 3D shapes or a whole building or assembly (in the project context) with Revit (in the family editor environment). Prefabricated solid objects or imported geometric models can be used with modeling tools. Except for some object categories like roofs, slabs, terrain, and the massing environment, Revit is a modeller and does not allow you to alter the individual polygons of an item. In addition to being able to import pre-existing models, an expert user may also construct realistic and accurate families spanning the gamut from furniture to lighting fixtures. Parametric models with dimensions and properties can be used to generate Revit families. To alter a specific component, users can

simply alter its established characteristics, like its height, width, or number in the case of an array. A family creates a geometry whose appearance is determined by a set of parameters; each possible parameter combination is then saved as a type; and additional variants can be added to each instance of a type. Finally, the additional and non-symmetrical conditions will be added in addition to the roof and first floor of the building as in Figure (3.6).

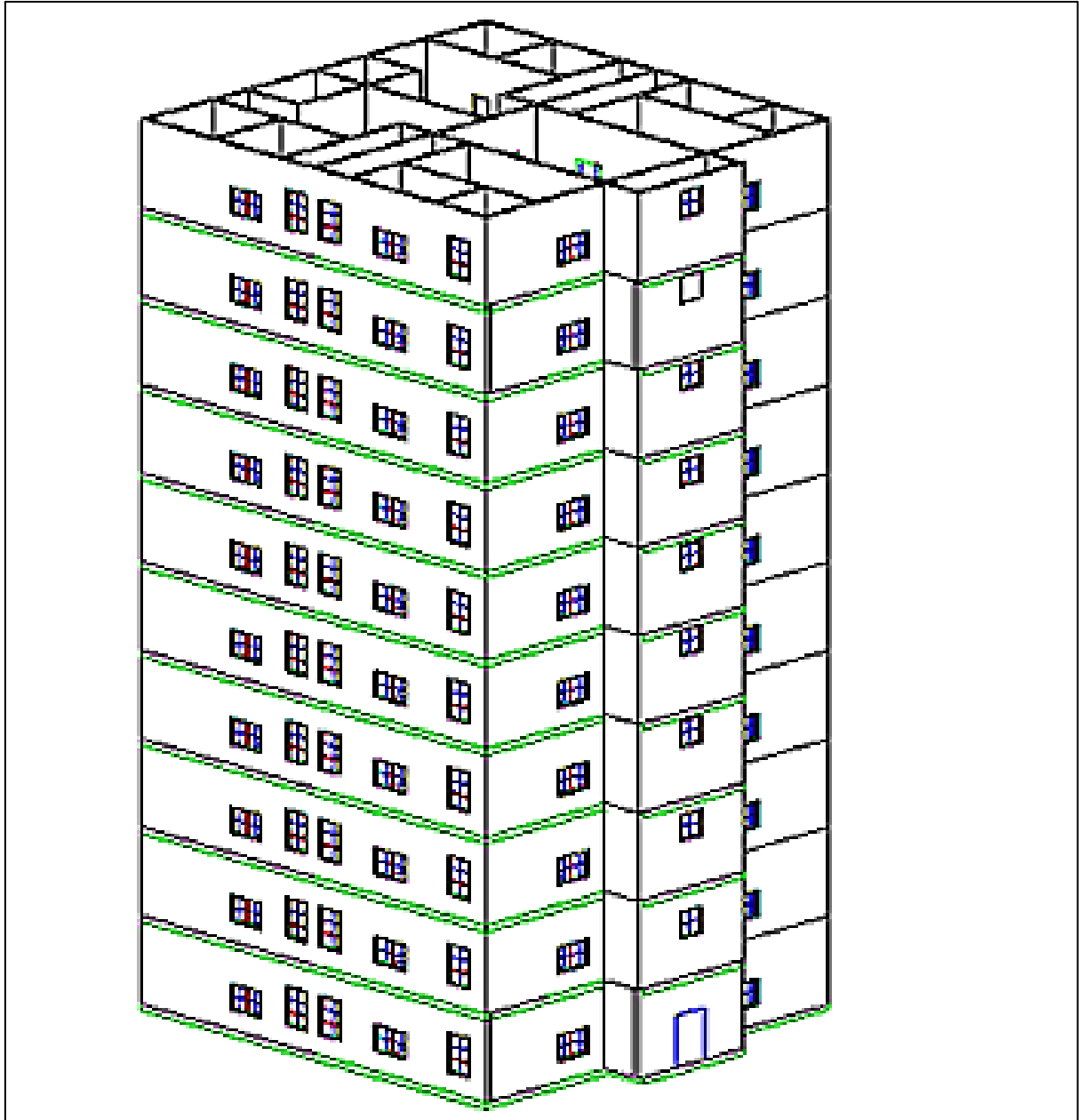


Figure 3.6: Adding the non-symmetrical elements to the building.

After completing the building, the bill of quantities will be taken from the software. This essential bill of quantities is listed in Appendix (A to D).

3.4 PROPOSED SUPPORT VECTOR MODEL

A supervised machine learning approach, support vector machine (SVM) can tackle both classification and regression issues. It's useful for solving both linear and nonlinear problems, and it generally performs well in practice. The basic premise of SVM is this: In order to categorize the data, the algorithm generates a line or hyperplane. It is possible to use an extension of the Support Vector Classification approach to address regression issues. Support vector regression is the name for this strategy. Since the cost function for constructing the model does not care about data points that lie beyond the margin, the model generated by support vector classification only depends on a subset of the used data. Similarly, Support Vector Regression only uses a portion of the raw data to create a model, as the cost function does not take into account samples that are close to the target when calculating the cost. Support Vector Machines can be divided into two categories:

- a. Linear SVM, also known as Simple SVM, is used for data that can be neatly separated along a linear axis. When a dataset can be neatly divided into two categories using only a straight line, we say that it is linearly separable, and we use the term "linear SVM classifier" to describe the resulting classification model. It is most frequently employed in the contexts of linear regression and classification issues.
- b. Nonlinear support vector machines (svms) are used to classify data that is not linearly divided. In this scenario, a nonlinear support vector machine (SVM) classifier is employed. Because additional characteristics may be added to match a hyperplane rather than a two-dimensional space, it is more adaptable to nonlinear data.

Accurate model prediction of cost time series data generated by linear approaches is frequently impossible. The use of linear estimate approaches is not practical in the construction sector [61–65]. The uses of cost data in building projects are intricate and nonlinear. Therefore, it is vital to create cutting-edge methods like artificial intelligence for estimating time series data in these projects because typical linear estimate techniques

are not appropriate. This research reports on the cost estimate of these projects by proposing a new intelligent model built on two potent methodologies to solve the shortcomings of the commonly used strategies.

3.4.1 Support Vector Machine

Vapnik built the first SVMs on the back of SLT in the late 1960s. However, from the middle of the 1990s, as more computer power became available, the algorithms used for SVMs began to emerge, opening the door for several real-world applications with significant outcomes [65]. As shown in Figure (3.7) [66], the basic SVM works with two-class issues where the data are divided by a hyperplane that is specified by a set of support vectors. For the sake of thoroughness, a basic introduction to SVM is provided below. Readers can refer to the SVM tutorials [67] for detailed descriptions. The least squares support vector machines (LS-SVM) is a new training technique based on the SVM; however, it requires only the solution of a set of linear equations instead of the long and computationally hard quadratic programming problem involved in the standard SVM. The LS-SVM works with the least squares cost function [68].

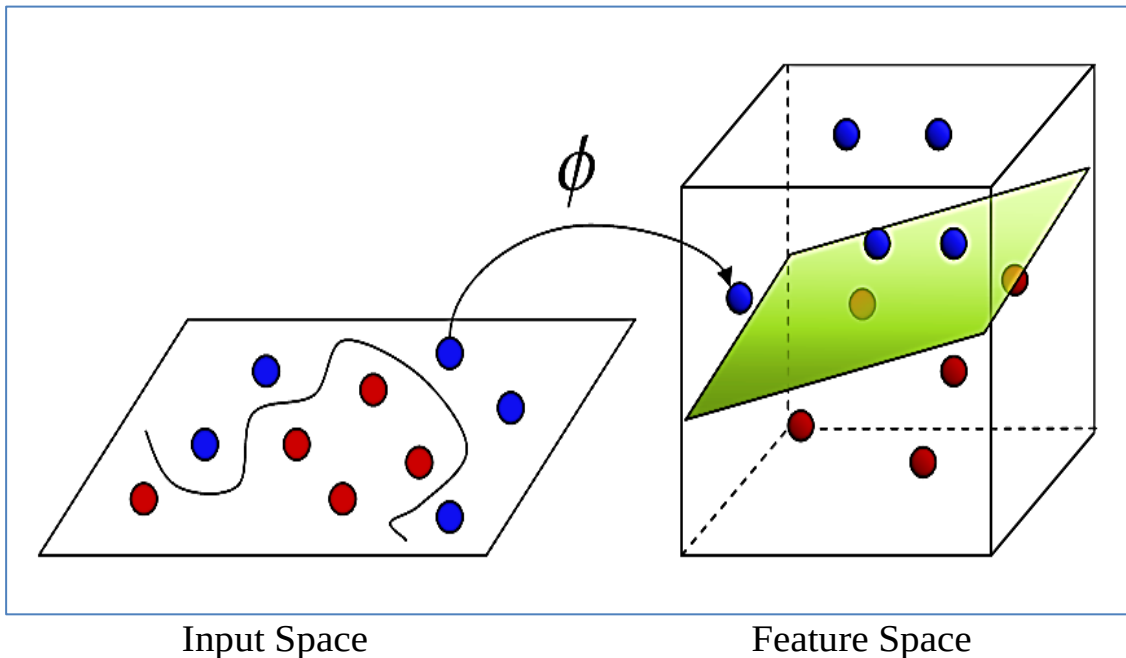


Figure 3.7: Nonlinear SVM [66].

Classification: The SVM's goal is to learn a separate function that divides training cases into various groups based on their assigned class labels. According to this perspective, SVMs are a type of supervised learning model that is mostly used to solve classification and regression issues [69]. SVM models created in the new space can express a linear or nonlinear decision boundary in the old space by translating input vector x into a high-dimensional feature space. The hyperplane with the maximum distance to the closest training examples is used to create an ideal separation between instances of different classes in the new space. SVMs are therefore thought of as a method that creates the maximum margin hyperplane to show the maximum separation between different classes. The cases that are closest to the maximum margin hyperplane for a given learning issue uniquely illustrate it, and these instances are referred to as support vectors. Additionally, the distinct function might be either linear or nonlinear. If the cases are linearly separable, a linear hyperplane may be used to split them; if not, the case is nonlinearly separable [69].

Consider a given set S with n labeled training instances: $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ for the linearly separable case. Each training instance $x_i \in R^k$, for $i = 1, \dots, n$, belongs to one of the two classes in comparison to its label $y_i \in \{-1, +1\}$, where k is the input dimension. The following equation may be used to explain the greatest margin hyperplane:

$$y = b + \sum w_i y_i x(i) x \quad (3.1)$$

Where denotes a dot product, a test example is represented by the vector x , and support vectors are represented by the vectors $x(i)$ s. The parameters, b and w_i in this equation, which determines the hyperplane, must be learned by the SVM. The following convex quadratic programming (QP) issue must be resolved to produce an ideal hyperplane:

$$\begin{aligned} &\text{Minimize } \frac{1}{2} \|w\|^2 \\ &\text{Subject to } y_i(w x_i + b) \geq 1 \quad i = 1, \dots, n \end{aligned} \quad (3.2)$$

where the kernel function is defined as $K(x(i), x)$. There are several kernels available for creating the inner products needed to construct SVMs with various nonlinear decision

surfaces. The most often used kernel functions are the Gaussian radial basis function $K(x, y) = \exp(-1/\delta^2(x - y)^2)$ and the polynomial kernel $K(x, y) = (xy + 1)^d$

where d is the degree of the polynomial kernel and δ^2 is the bandwidth of the Gaussian radial basis function [69].

Regression: The above-described maximum margin hyperplane is exclusively employed in categorization. However, a version of the SVM for regression has been included in the SVMs, which have been created for general estimation and prediction applications (LS-SVM). By reducing the prediction error, LS-SVM seeks to identify a function that accurately approximates the training examples. By simultaneously attempting to maximize the flatness of the function, the danger of over-fitting is reduced when the error is minimized. One must once again resolve the following quadratic programming issue to identify an ideal hyperplane:

$$\begin{aligned} \text{Minimize } & \frac{1}{2} \|w\|^2 \\ \text{Subject to } & \|y_i (w \cdot x_i + b)\| \leq \varepsilon, \end{aligned} \quad (3.3)$$

Where the value $\varepsilon \geq 0$ is the prediction error bound. If $f = \langle w, x \rangle + b$ genuinely exists and approximates all pairs (x_i, y_i) with ε precision, then the aforementioned convex optimization problem will be achievable. The following optimization problem has restrictions that are ordinarily impossible to satisfy, thus one inserts slack variables φ_i, φ_i^* to deal with them:

$$\begin{aligned} \text{Minimize } & \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\varphi_i, \varphi_i^*) \\ \text{Subject to } & \begin{cases} y_i - \langle w, x_i \rangle - b \leq \varepsilon + \varphi_i \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon + \varphi_i^* \\ \varphi_i, \varphi_i^* \geq 0 \end{cases} \end{aligned} \quad (3.4)$$

The trade-off between f flatness and the maximum allowed deviation, ε , is calculated using the constant C . This optimization problem may be built as a dual problem by building the Lagrangian function:

$$L = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\varphi_i, \varphi_i^*) - \sum_{i=1}^l \lambda_i (\varepsilon + \varphi_i - y_i + \langle w, x_i \rangle + b) - \sum_{i=1}^l \lambda_i^* (\varepsilon + \varphi_i^* - y_i + \langle w, x_i \rangle - b) \text{ and } \lambda_i, \lambda_i^* \geq 0 \quad (3.5)$$

Solving the Lagrangian, one provides the optimal solutions w^* and b^* :

$$\begin{aligned} b^* &= y_i - \langle w, x_i \rangle - \varepsilon, \quad 0 \leq \lambda_i \leq C, \quad i = 1, \dots, l, \\ b^* &= y_i - \langle w, x_i \rangle + \varepsilon, \quad 0 \leq \lambda_i^* \leq C, \quad i = 1, \dots, l \end{aligned} \quad (3.6)$$

For nonlinear issues, the inner products can be changed by appropriate kernels, much like in classification. Enforcing the upper limit C on the absolute value of the coefficients w_i s allows us to keep an eye on the trade-off between reducing prediction error and maximizing the flatness of the regression function. The upper limit, a parameter that the user must set in addition to ε , will limit the impact of the support vectors on the form of the regression function. The function may match the data more closely the greater C is. The approach essentially does the least absolute-error regression with the coefficient size restriction in the degenerate situation where $\varepsilon = 0$, and all training examples will be support vectors. In contrast, if ε is big enough, the error decreases to zero, and the algorithm returns the flattest curve that contains the data, regardless of the amount of C [69-71]. In contrast, if C is big enough, the error decreases to zero, and the algorithm returns the flattest curve that contains the data, regardless of the amount of ε .

3.4.2 Cross-Validation Technique

One well-known method for calculating generalization errors is cross-validation [72]. In this study, the k -Fold cross-validation method is considered among other cross-validation methods. One method to improve the holdout approach is K -Fold cross-validation. The holdout approach is used for each of the k subgroups of the dataset. One of the k subsets is used as the test set each time, while the other $k - 1$ subsets are taken into account to produce the training set. The average error across all k trials is then determined. This method's key advantage is that it doesn't matter how the data is divided.

Each data point appears precisely once in the test set and appears in the training set $k - 1$ times. As k is raised, the variance of the resultant estimate decreases. This approach may be modified by randomly dividing the data into test and training sets k times. The k-fold cross-validation method demonstrates how neural network topologies may be used to make an optimum generalization. Three-fold and ten-fold cross-validation methods were recommended to estimate real-world applications in the relevant literature [73].

3.4.3 Steps of Proposed Intelligent Model

The LS-SVM and cross-validation are two potent approaches that serve as the foundation for the suggested model. In this model, the LS-SVM is used as a supervised learning tool to manage input-output mapping and focuses on the characteristics of cost data in construction projects. The k-fold cross-validation is used to train the LS-SVM to provide a more realistic evaluation of the accuracy by dividing the entire dataset into multiple training and test sets, as well as to provide reliable results. The suggested intelligent model may be a combination that is computationally effective and appropriate for estimating building projects' costs. The following are the steps of the suggested model: Stage 1: Separating the data into training and test sets. The training set is used to build the LS-SVM model, while the test set is used to assess the model's performance.

Stage 2: Training information Sequential data are used by the model as training data. In this stage, the training data are normalized into the same range (0, 1) and the sequential data reflects the specified qualities to assist prevent numerical issues. The following illustration shows the function used to normalize data:

$$x_{sca} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (3.7)$$

The result of this transformation is that all the variables have no dimensions.

Stage 3: LS-SVM Training The LS-SVM is used in this stage to manage input-output mapping. As a logical option, the Gaussian radial basis function kernel is used [61 and 69]. The LS-SVM training is carried out to create the prediction model utilizing the k-fold cross-validation method on the training data set.

Fitness definition: Chen and Wang [70] assert that although the training dataset's fitness may be easily calculated, it is prone to over-fitting. The k-fold cross-validation method is used to address this issue. This method builds the regression function with a given set of parameters (C_i, δ_i) by utilizing $k-1$ subset as the training set after randomly splitting the training dataset into k subsets. The last set is regarded as validation. The previous process is carried out k -fold times. Consequently, the MAPECV of the k-fold cross-validation method on the training dataset serves as the definition of the fitness function:

$$Fitness = \min f = MAPE_{cv}, \quad (3.8)$$

$$MAPE_{cv} = \frac{1}{l} \sum_{j=1}^l \left| \frac{y_j - \hat{y}_j}{y_j} \right| \times 100\% \quad (3.9)$$

where y_j is the actual value; $\hat{y}_j$ are the validation value and l is the number of subsets. The solution with a smaller $MAPE_{cv}$ of the training, the dataset has a smaller fitness value.

Stage 4: The LS-SVM parameters are supplied in this stage so that the estimations may be made. Choose the best parameter settings to construct the LS-SVM model. All of the following regression models estimate the effective factors on building cost using the MATLAB (see Appendix E) function predict (mdl,valid), where mdl is a MATLAB model object holding the regression model and valid is the validation data set.

Stage 5: LS-SVM model with the test dataset substituted to achieve the estimation values. Through testing performance, it is possible to validate the LS-SVM model's estimated capacity by taking into account performance criteria to compute the error between real and estimates values. The structure of the suggested intelligent model is shown in Figure (3.8). To reduce the MAPECV during prediction iterations, this model is used to try to optimize the LS-parameter SVM's combinations.

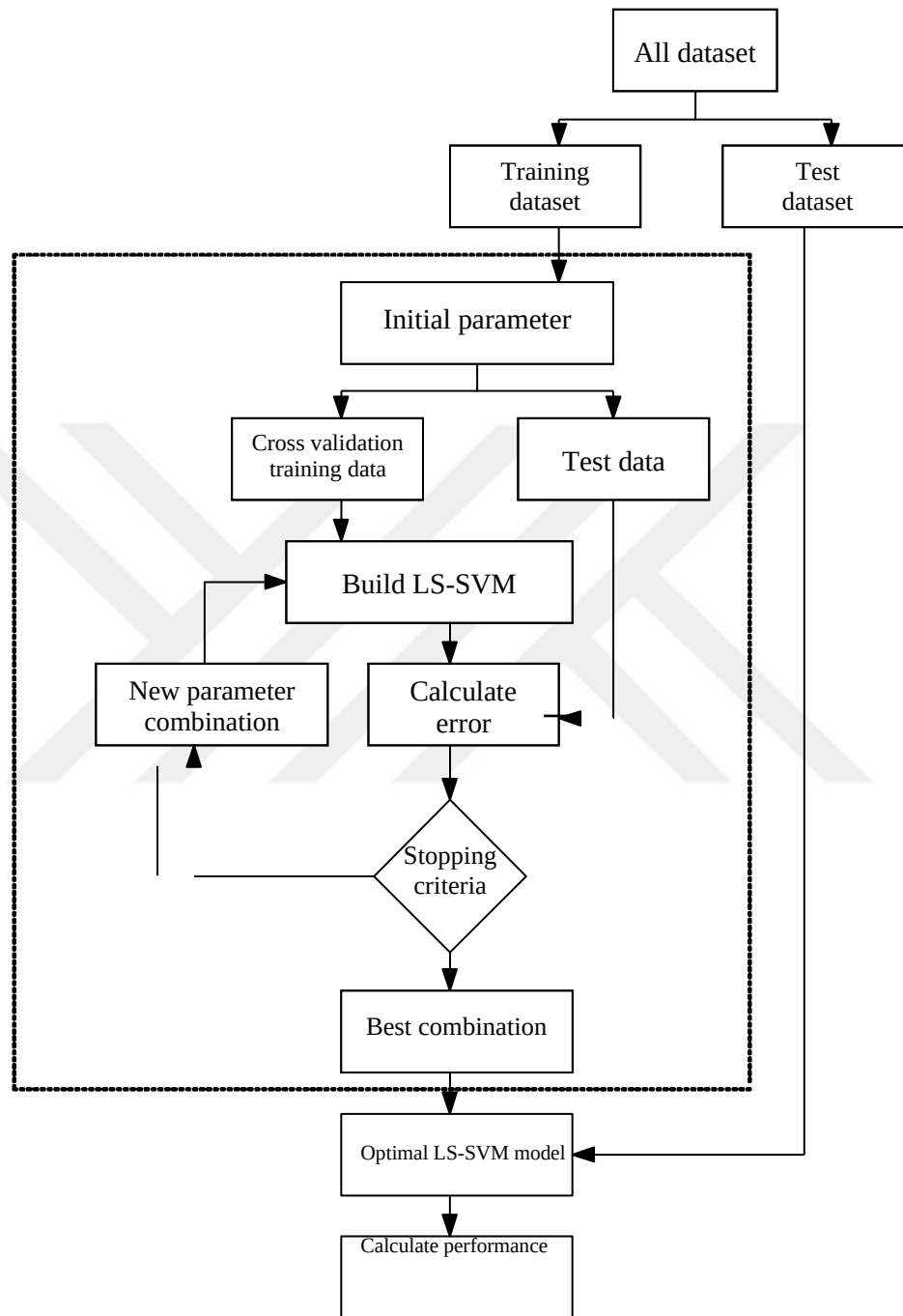


Figure 3.8: The proposed LS-SVM model.

3.5 EVOLUTIONARY FUZZY NEURAL INTERFACE MODEL

The majority of issues in construction management are complicated, unclear, and environment dependent. Neural networks, fuzzy logic, and genetic algorithms have all been effectively used in construction management to address a variety of issues. These three computing techniques make up for one paradigm's shortcomings with those of the other two. Cheng [1] uses the aforementioned three methods, taking into account the strengths of each strategy, to create an Evolutionary Fuzzy Neural Inference Model (EFNIM). The optimum adaptation mode is automatically determined in the model since GAs is primarily concerned with optimization, FL with imprecision and approximation reasoning, and NNs with learning and curve fitting. Figure (3.9) depicts EFNIM's architecture. The FL, NN, and GA paradigms are combined to form the proposed EFNIM. The benefits of one paradigm were balanced out by the others when FL, NNs, and GAs were used together. FL, NN, and GAs are largely focused on learning and curve fitting in the formulated model, whereas FL, NN, and GAs are mostly focused on imprecision and approximation reasoning. Technologies FL and NNs complement one another. The integration of these two technologies into a single system looks to be a promising step toward the creation of intelligent machines that can mimic the functions of the human brain. The classic fuzzy logic system's fuzzy rule base and fuzzy inference engine are replaced by the NN in Figure (3.9). The NN is employed to provide the integrated system with a learning capability and to get around challenges in acquiring fuzzy rules and determining composition operators. A "neuro with fuzzy input-output," also known as a neural network with both fuzzy inputs and fuzzy outputs, is a combination of the FL and NN. For ease of use, the "neuro with fuzzy input-output" in this work is initialized by the FNN, a broad term to indicate the fusion or union of FL and NN. The FNN for learning various tasks has shown difficulty in selecting an acceptable topology as well as adequate parameters for human inference, although the FNN is more reasonable than classic FL to imitate the features and process of human reasoning. Additionally, choosing an appropriate distribution for the MFs to solve various issues takes time, and the difficulty rises with problem complexity. GA is a successful strategy for overcoming FNN's shortcomings. To concurrently find the best FNN topology, best FNN parameters, and fittest MF forms, EFNIM uses GA.

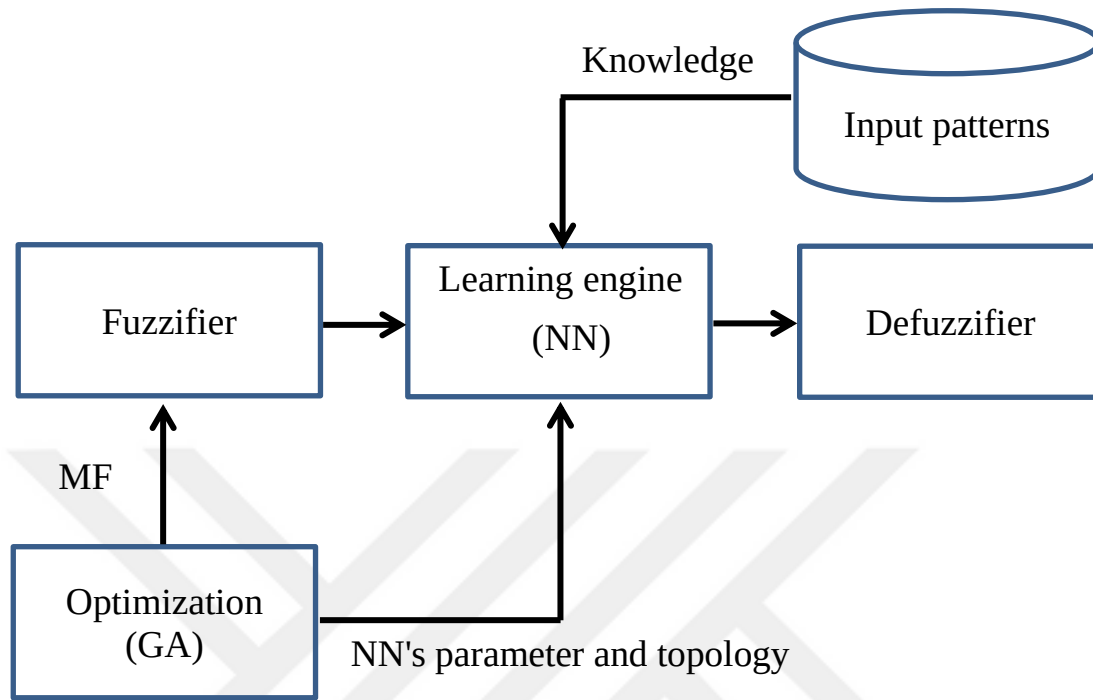


Figure 3.9: EFNIM Architecture [1].

3.6 MODEL VALIDATION

The proposed model based on the LS-SVM with a cross-validation approach is applied to the available dataset based on the real data reported in to assess its efficacy [74]. The conceptual phase of a construction project's cost is affected by 10 elements in this dataset. Site studies and the owner's preliminary needs can be divided into two primary categories. These input patterns are from actual group initiatives in Taiwan between 1997 and 2001 [74].

The descriptions of these patterns are as follows: (1) Site area (in square meters); (2) Geology property; (3) Influencing householder number; (4) Earthquake impact; (5) Planning householder number; (6) Total floor area (in square meters); (7) Floor over ground (in stories); (8) Floor underground (in stories); (9) Decoration class; (10) Facility class; and (11) Normalized cost of the building project.

40 building models are used as an actual community housing complexes with reinforced concrete buildings that will be built in the central region of Iraq (Baghdad, Hilla, Karbala and

Alnajaf) between 2015 and 2022. The dataset contains 32 rows of data, of which 8 rows are chosen to evaluate the suggested intelligent model as well as two well-known methods, namely Nonlinear Regression (NR) and Evolutionary Fuzzy Neural Interface Model (EFNIM). The sequential data is then used by the model as training data. In the training phase, a cross-validation approach is used to address the issues caused by the short training dataset.



4. RESULTS AND DISCUSSION

4.1 COLLECTING DATA

The term "data collection" refers to the organized gathering of information by observation or measurement. Whether you're doing a study for the government, a corporation, or a university, collecting data is the key to getting a leg up on the competition. The term "data collection" refers to the act of amassing relevant information from a variety of resources for the purpose of assessing potential outcomes, such as the resolution of research problems, the identification of trends and probabilities, etc. If you want to learn more, scroll down. Deciding what kind of formal structure best conveys the underlying qualitative and quantitative concepts being employed in a specific study is essential in constructing representations of the data that are both accurate and valuable. If you take the time to carefully organize and develop your data collection process, you'll end up with better results. The first step in monitoring or evaluating an intervention is deciding what kind of information will be collected and how it will be used. In addition to considering the review's context, existing limits, access, scheduling, money, and availability of data, selecting an acceptable approach will also allow for a suitable assessment of the monitoring or evaluation questions guiding any review. Data validity and reliability can be ensured by paying attention to the following aspects of data collection planning: the data's intended use, the data collection's intended methodology, the data collection's intended resources, and the data collection's intended time. In that regard, either a qualitative or quantitative method of data collection, or a combination of the two, can be explored. The questions answered will have a major impact on the processes of information collection, analysis, and evaluation. The effectiveness of a survey depends on more than just the choice of questions; it also depends on the investigation of several approaches to achieving the intended outcomes. The first step is to put the survey's results and conclusions ahead of the survey's execution. Identifying the nature of the data at hand is the first step in ensuring it is used effectively. An effective survey must begin with a clear mental picture of the finished product. The consultant managers were 35 persons, 15 engineers with experience about 20 years and 20 engineers with experience between 10 and 20 years as shown in Table (4.1).

Table 4.1: The Distribution of Questionnaires

No.	Job title	No. of engineers
1	consultant managers	35
2	engineers with experience about 20 years	15
3	engineers with experience 10 to 20 years	20

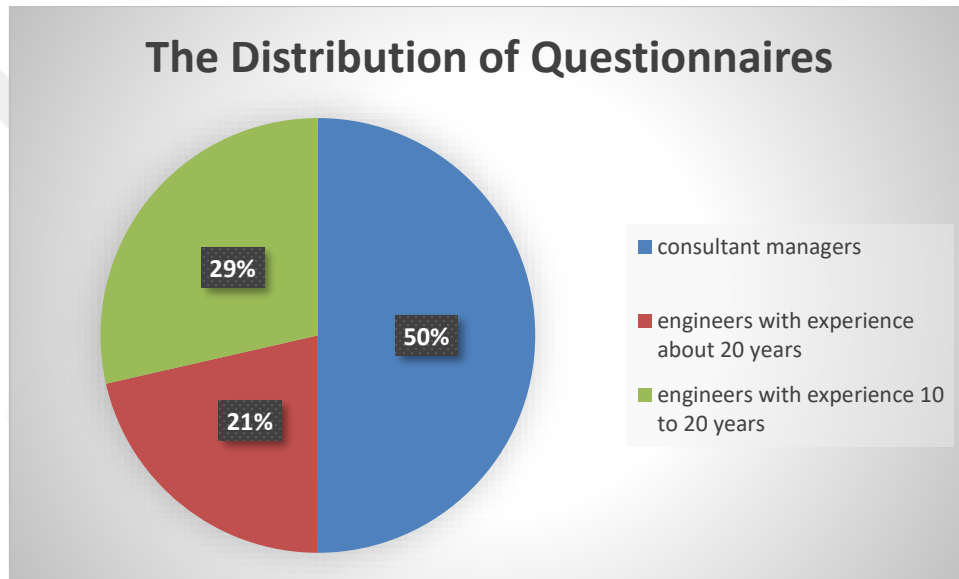


Figure 4.1: Distribution of questionnaire percentage.

4.2 QUESTIONNAIRE RESULTS

There were a total of five questions on the survey, and their construction allowed the researchers to collect both quantitative and qualitative data, such as respondents' preferences (as indicated by their selection of a particular response option) and their rationales (provided in the accompanying free-text space).

4.3 LABOR PRODUCTIVITY RESULTS

Workforce productivity, or labor productivity, is the rate of economic growth expressed in terms of output per worker hour. The rate of labor productivity growth is calculated as the

annualized rate of change in economic output per worker hour. Employee productivity, which looks at how much each person contributes, should not be confused with labor productivity. Increases in labor productivity lead directly to increasing consumption, which in turn raises living standards. More goods and services are produced for the same amount of work when labor productivity rises. As production rises, so does the affordability of the goods and services it produces. Changes in physical capital, cutting-edge technology, and human capital are the primary drivers of labor productivity expansion. In most cases, improvements in any one of these three categories will be the driving force behind rising worker productivity. What we mean by "physical capital" here is the tools, equipment, and buildings that are at the disposal of employees in order to create things. New technologies, including assembly lines and automation, are ways to maximize output by maximizing input. The rise in human capital reflects the rise in the proportion of the working population with advanced degrees and/or areas of expertise. One way to approximate the total impact of these tendencies is through measuring worker productivity. Increases in labor productivity may signal a temporary improvement in the economy's health or perhaps a turnaround. If output rises while hours worked stay the same, then means workers have gotten more productive. In addition to the aforementioned three variables, this is also observed during economic recessions, when workers put in more hours to avoid being laid off as unemployment rises. The independent factors for Labor productivity presented in Table (4.2).

Table 4.2: The independent factors for Labor productivity

F1	Work scheduling method
F2	Number of supervisors
F3	Worker's experience
F4	Change task type

The Labor productivity factors affect quantity per floor and floor heights in different ways as in below.

Building a multistory structure involves a lot of work that is the same on each level. Neither the ground floor nor the penthouse may see worker output at or near 100% of the usual. Nonetheless, there might be a trend in worker productivity as construction goes on. Using data from the project logs, we can calculate the productivity of the workers engaged in the rebar and formwork processes. This study did not include a basement in its productivity analysis since its conditions were so different from those on other floors. In line with prior research. So, structural activities have similar productivity. Floor 1 is fairly similar to Floor 10 in terms of layout. The results of Labor productivity factors effect shown in Figures (4.2 to 4.5).

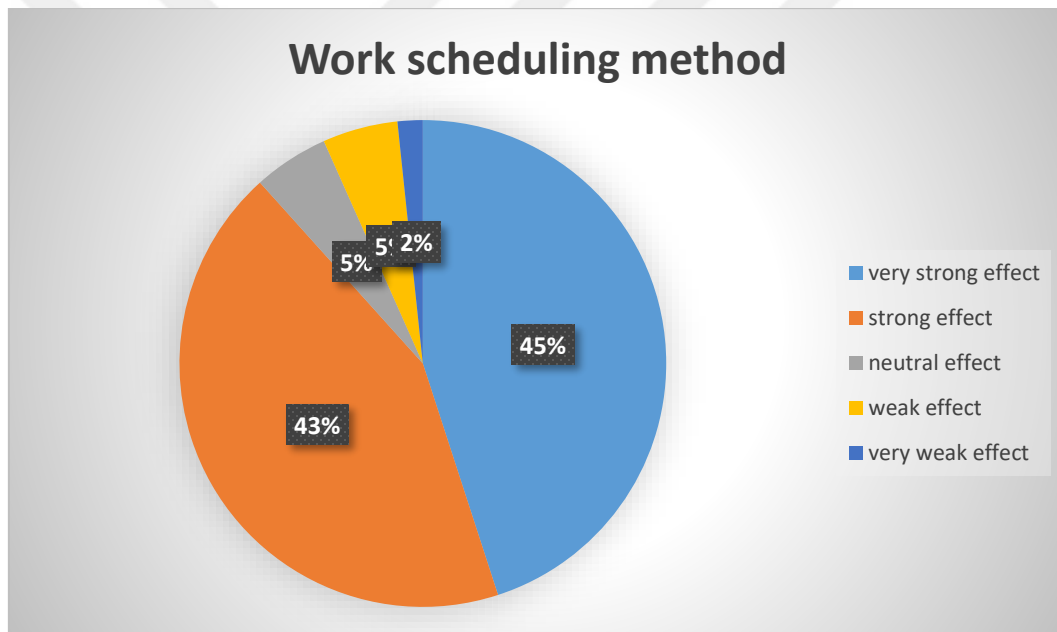


Figure 4.2: Work scheduling factor effect on quantity per floor.

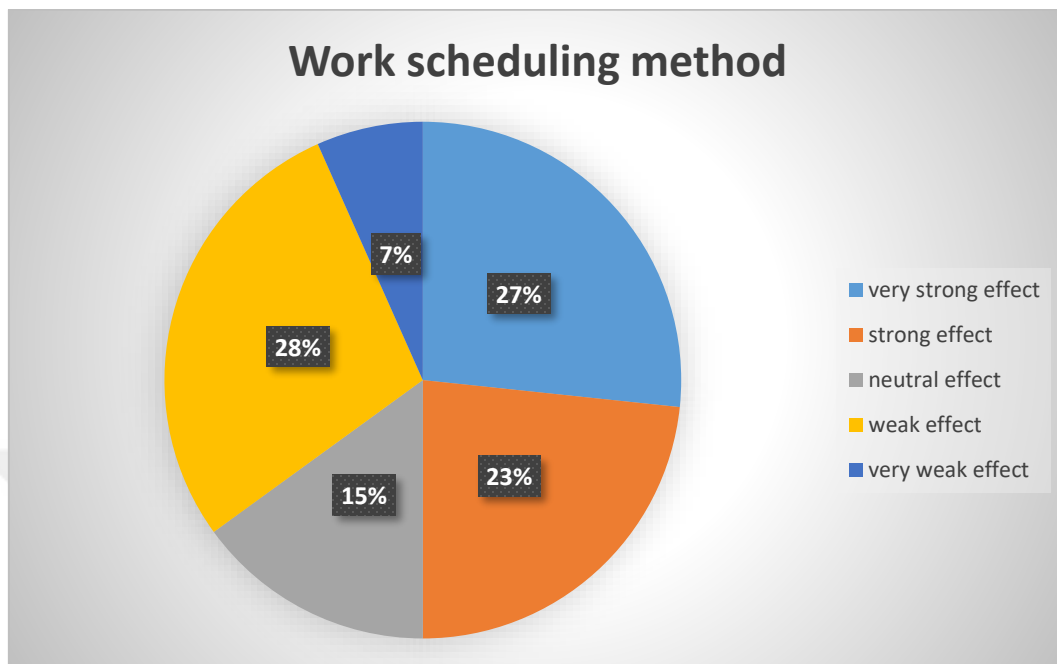


Figure 4.3: Work scheduling factor effect on Floor height.

Work scheduling methods are crucial because without them, work cannot be completed in a timely manner or to the needed quality. As a result of poor management, insufficient job scheduling, and consequently slow productivity, this aspect was rated as extremely strong by 45% of respondents. Additionally, the project manager's failure to account for realistic worker capacity led to an inadequate time schedule for the project. When an employee is expected to be present and actively engaged in work is referred to as their "work schedule." In most workplaces, this is predetermined by the employer and consists of a certain number of days and hours per week. Scheduling employees requires careful planning in order to meet everyone's demands, accommodate individual preferences, and maximize productivity. But that's not all: you also have to maximize productivity while controlling expenses by observing any and all labor laws and regulations that may pertain to your business. An organization's ability to communicate with its hourly workers is greatly aided by the availability of employee schedules. In businesses that rely heavily on human labor, careful planning of personnel schedules is key to satisfying production objectives and achieving other important corporate goals. An efficient shift schedule is the basis for a win-win result, as evidenced by productive operations and a devoted team.

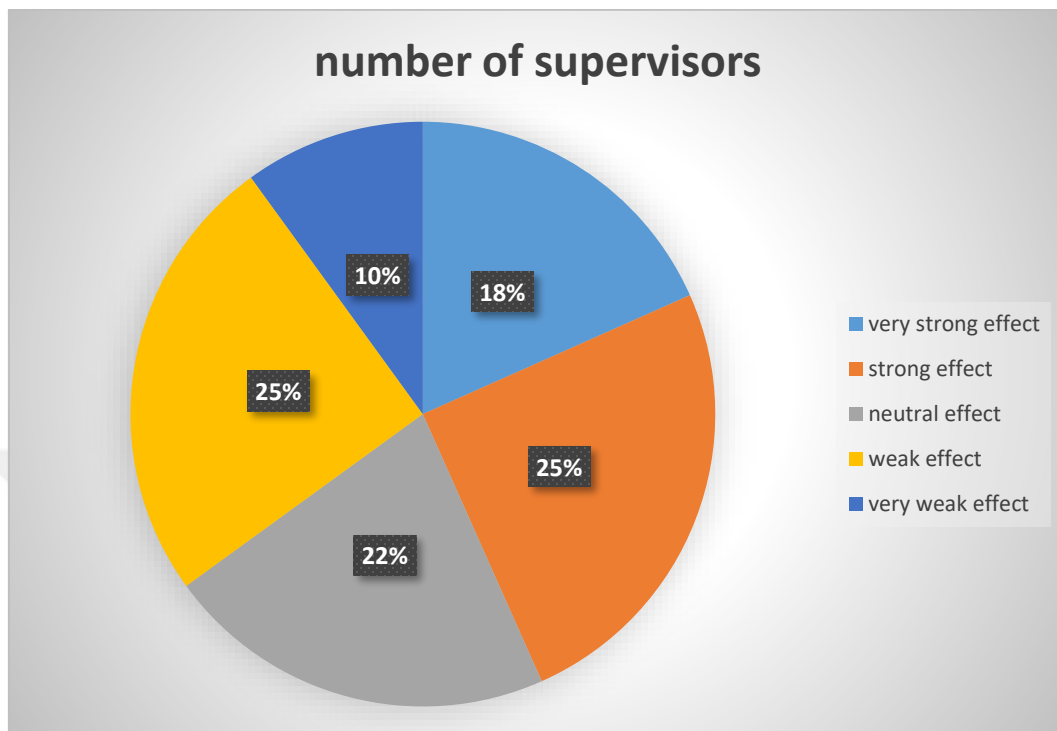


Figure 4.4: Number of supervisor factor effect on quantity per floor

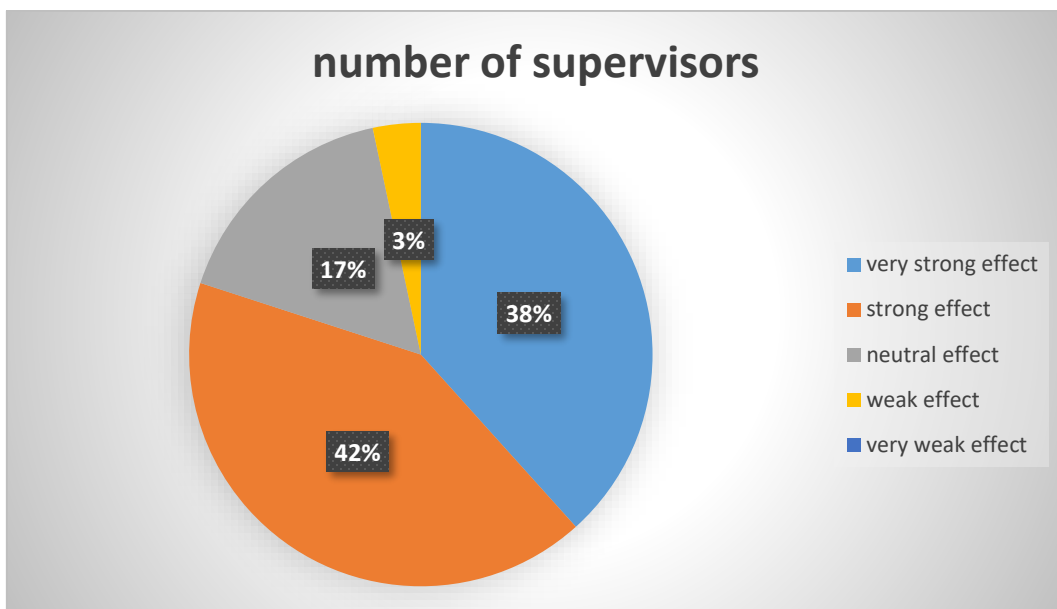


Figure 4.5: Number of supervisor factor effect on Floor height

When discussing organizational structures, the term "span of control" is frequently used to refer to the number of employees to each supervisor. This pertains to how many workers a manager can supervise efficiently. The concept of "span of control" is crucial in the corporate world, as problems can arise when a single manager is responsible for too many personnel. Executives need to focus on expanding managers' spheres of influence to prevent these problems from arising. Managers are able to properly oversee the appropriate amount of workers when there is an appropriate supervisor-to-staff ratio in place. There are a number of elements that go into deciding how many managers are assigned to each employee. Management skills, the tasks performed, and employee expertise all play a role in determining the level of authority each employee has inside an organization, and thus the level of authority each supervisor has over them. Managers that are knowledgeable and can clearly articulate their expectations to their staff are effective across a broad range of responsibilities. When dealing with inexperienced workers who lack the ability to complete job obligations without direct supervision, it is vital to set a limited span of control. Workforce members whose tasks are routinely performed benefit from a high level of managerial autonomy. Positions with a limited scope of control are ideal for workers whose jobs demand specialized expertise and close supervision, as presented in Figures (4.6 and 4.7).

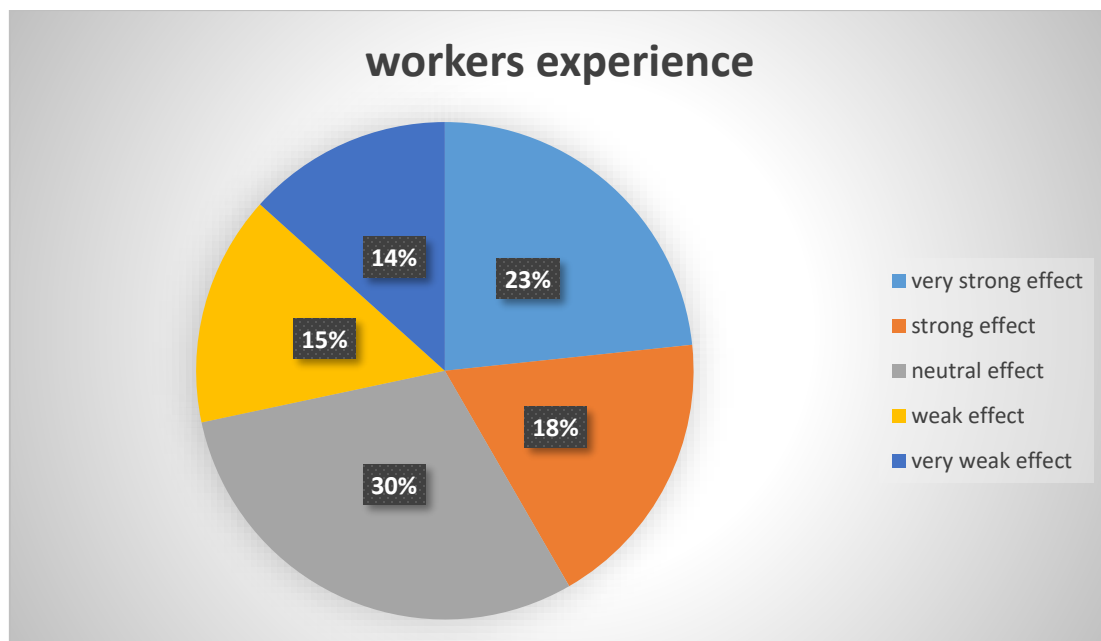


Figure 4.6: Workers experience factor effect on quantity per floor.

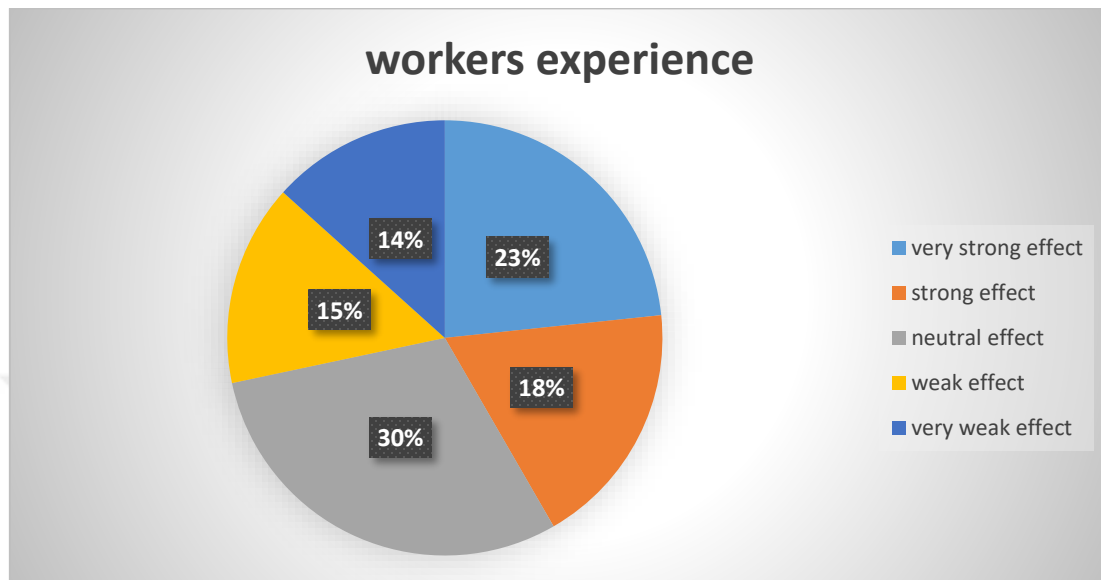


Figure 4.7: Workers experience factor effect on Floor height.

The term "employee experience" encompasses all aspects of a worker's time at the office, from contacts with their manager and coworkers to their use of company tools and collaboration with other employees. It's a comprehensive word that takes 23% of strong importance into account everything an employee goes through over their tenure with a company. Comparing employee experience to its more well-known counterpart, customer experience, can be a helpful starting point for comprehension. Just substitute the word "customer" with "employee" and you get a complete picture of the employee experience (Figures 4.8 and 4.9).

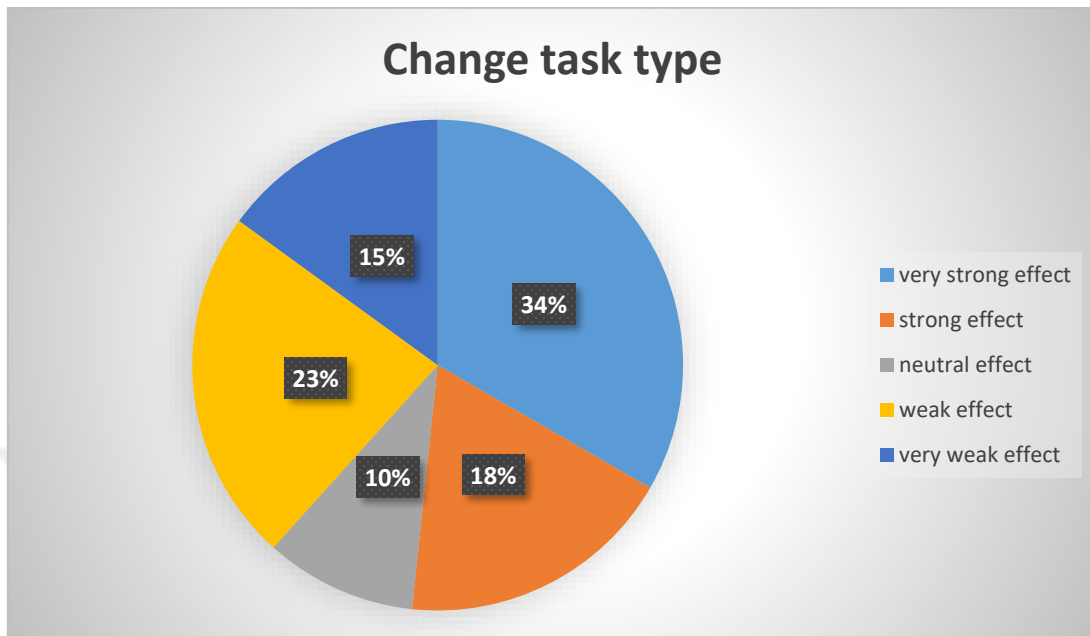


Figure 4.8: Change task type factor effect on quantity per floor

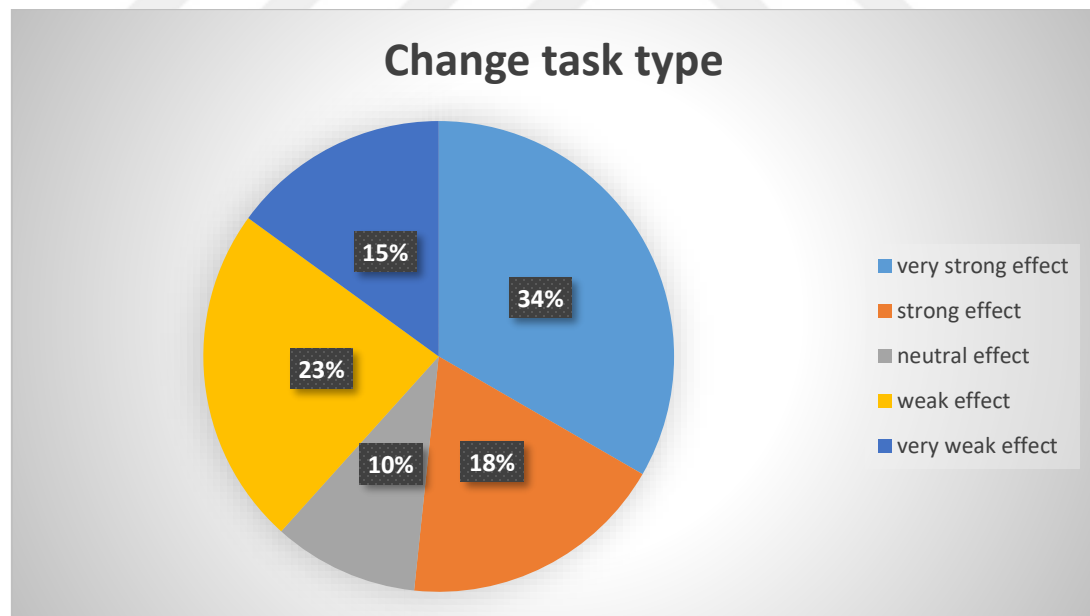


Figure 4.9: Change task type factor effect on Floor height

The effect on changing task type on project scheduling's primary function is to graphically depict how the project's scope will be delivered in stages throughout time. Simplistically, a project schedule is a calendar showing when certain events (often the completion of a

deliverable) are expected to occur. The unit labor cost is artificially inflated by the premium for overtime hours and the productivity loss associated with the total number of hours worked. The charts in this analysis show how working overtime increases costs and decreases output per worker. There is no universally applicable conclusion about the price of overtime. Time, the local labor climate, managerial actions, and the location of the project are all factors that contribute to the final price tag of any overtime work. Adaptation over lengthy periods of time allows workers to expend energy within strict parameters. There will be a period of readjustment whenever the number of hours worked per day or week is altered. According to research, the productivity of businesses that regularly engage in scheduled overtime drops dramatically in the first few days, but then recovers to a pretty normal level by the end of the first week. After this first phase of recovery, productivity may remain relatively stable for another two to three weeks before beginning a slow and steady fall over the subsequent four weeks. There is a further decline in productivity after five to six weeks of operations, which reaches a minimum after nine to twelve weeks of persistent overtime operation. It's important to keep in mind that this is only the outcome of natural responses and has nothing to do with external causes like hard work, harsh weather, or inept management.

4.4 EQUIPMENT PRODUCTIVITY RESULTS

Heavy machinery such as cranes, a passenger/cargo elevator, a trailer/lorry, a concrete pump, a truck mixer, and safety scaffolding are all present. This machinery is essential to the building process as a whole. Cranes, for instance, are essential for transporting and positioning formwork, hoisting and positioning reinforcement, and placing concrete. Material handling issues, as well as the slowing or stopping of activities, will result from any downtime experienced by the machinery. As a result, the accessibility of tools was seen as fundamental to the success of the building project. In reality, however, primary contractors typically supply only the bare minimum of tools and machinery at a job site in an effort to keep expenses down. When determining how much machinery would be needed, planners always look ahead to the best-case scenario, in which all industries are seamlessly interconnected, and no waiting or idling is required. As a result, everything is pooled together and scheduled for maximum efficiency. Although ideal conditions are hard to obtain in practice, no amount of preparation

can guarantee against the occurrence of an unexpected incident. As a result, most of the responders' criticisms have been about this phenomenon. As may be seen in Table (4.3), where determinants for equipment productivity are listed.

Table 4.3: Equipment productivity factors

F5	Equipment availability
F6	Equipment scheduling efficiency
F7	Maintenance quality
F8	Suitability of equipment to site requirements

The questionnaire results of equipment productivity are shown in the next section.

4.4.1 Equipment Productivity Factors Effect

Work cannot advance or be completed to the desired standard without the necessary tools being readily available. This issue, which is a result of poor management and includes factors such as insufficient provision of tools leading to inefficient use, the use of old and obsolete equipment, and a lack of spare parts, was rated by 40% as having a very strong effect. It was also noted that a bad project manager could be to blame if they overestimated the capacity of a machine and hence used too few of them (Figures 4.10 and 4.11).

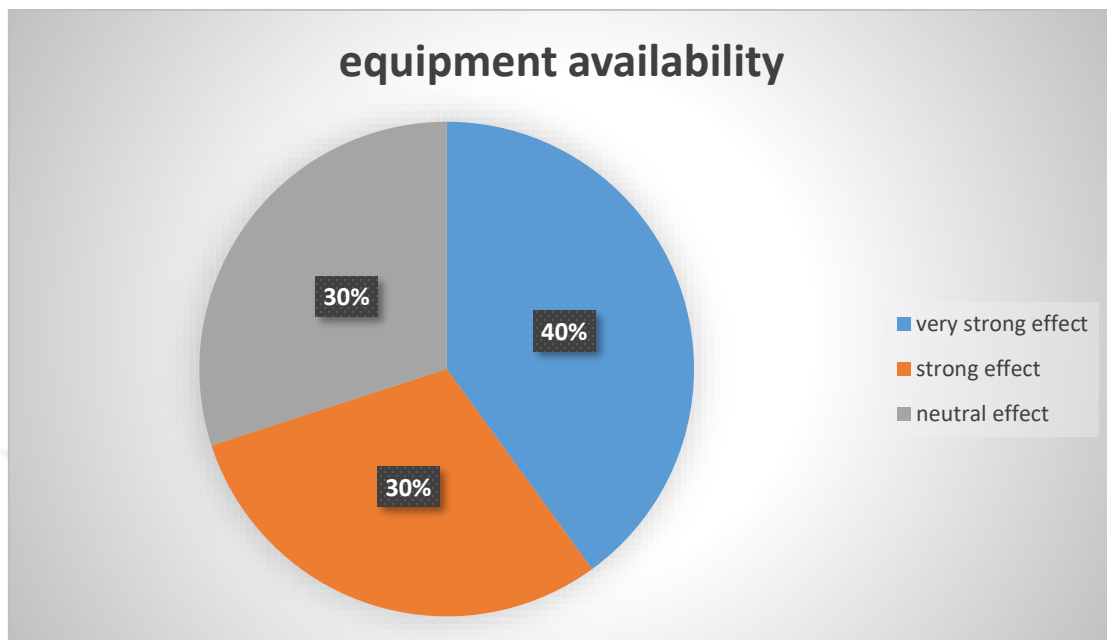


Figure 4.10: Equipment availability factor effect on quantity per floor.

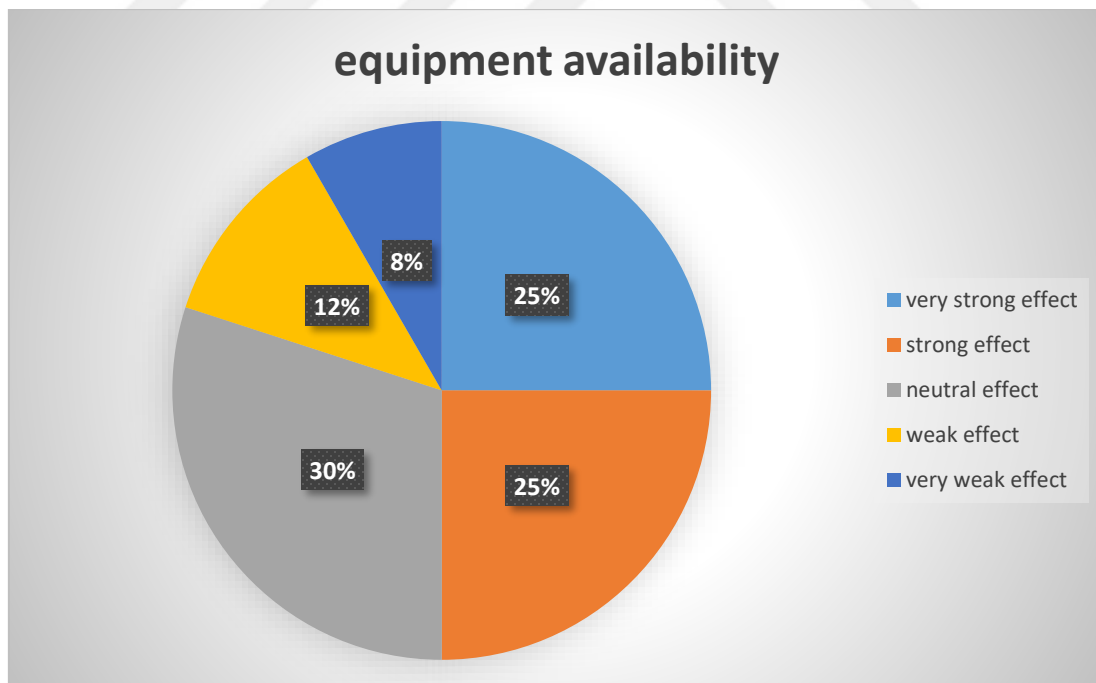


Figure 4.11: Equipment availability factor effect on Floor height.

Construction projects require the assignment of numerous types of machinery to individual duties. Since there is more work than resources, certain tasks will have to take precedence over others. There are numerous limitations on when, where, how long, and in what order the equipment can be assigned. Schedules must be applied manually by project managers, which is viewed as a major factor by 24 percent of specialists and consulting engineers. Processes like these necessitated thinking about massive volumes of data, which is simply too much for any one person to keep straight without some type of aide. There was no uniformity in planning because everything was done by hand (Figure 4.12). Even a seasoned professional would have trouble navigating the mountain of information necessary to create a reliable and high-quality timetable.

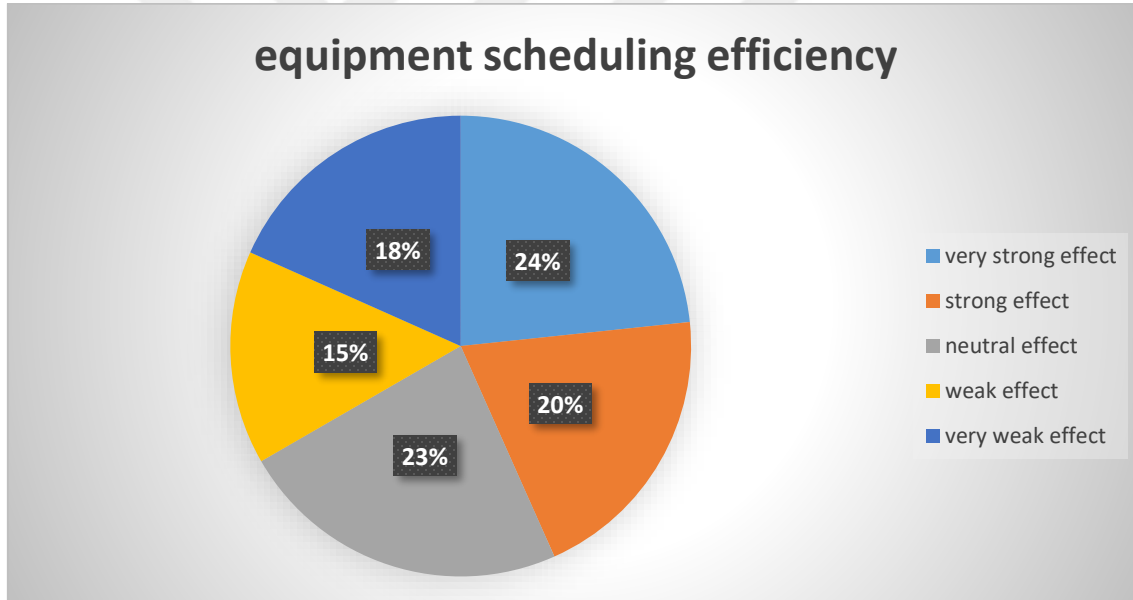


Figure 4.12: Equipment scheduling efficiency factor effect on quantity per floor.

Scheduling equipment ahead of time allows for more efficient project management and planning, which is especially useful while working on tall buildings. Phases of the project need to be mapped out, and the amounts and types of materials as well as any other resources that will be required to complete the task at hand should be considered. Here is where the scheduling of said equipment can prove useful. Without beforehand planning for the required machinery, this procedure is unable to carry out some portions of the project's tasks. The

project managers can then decide whether to wait for the item to become available or to rent or acquire a new tool to complete the task, based on the information provided by the effective equipment scheduling (Figure 4.13).

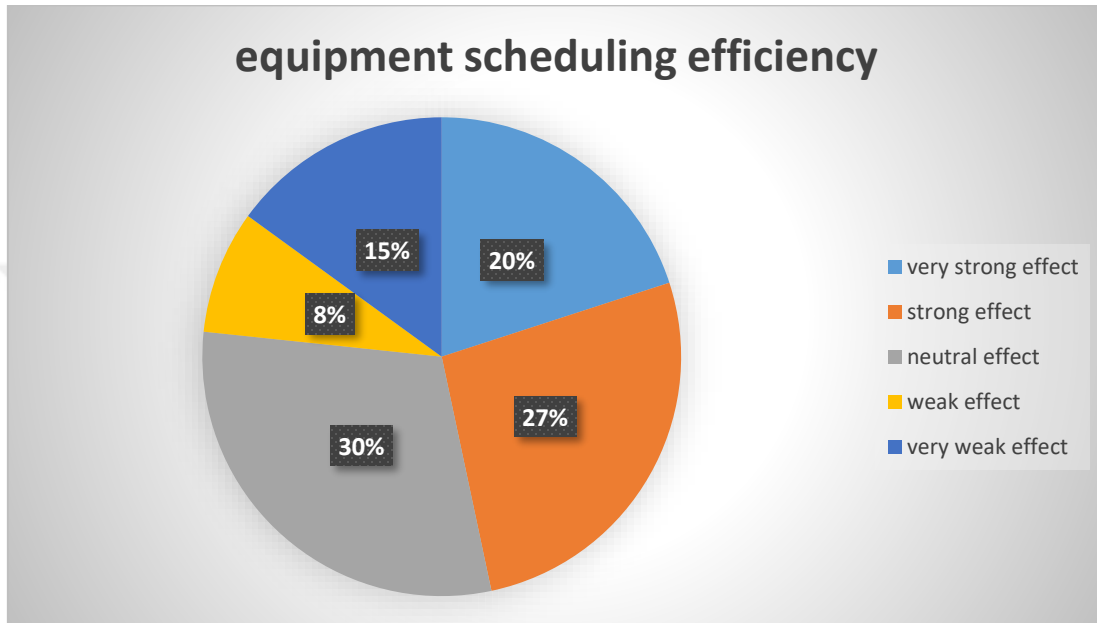


Figure 4.13: Equipment scheduling efficiency factor effect on Floor height.

The suitability of equipment to site requirements is another important factor. 34% of experts consider it a very important factor. Using the right tools for the job ensures that the job gets done quickly, efficiently, and without sacrificing quality or safety. Equipment used in the construction industry is crucial to the success of any building project. In other cases, the Contractor may not have access to or desire to purchase every piece of necessary Construction Equipment. Excavation, digging of enormous quantities of soil, transportation over quite long distances, placement, compacting, leveling, dozing, grading, hauling, etc. are all fundamental processes in the building of any Project. The building tools and machinery in use in India and overseas are listed here. The term "construction machinery," which also refers to the broader category of "construction equipment," encompasses a wide range of large machines employed in the construction sector. Loading and unloading materials, driving in and out materials and tools, moving materials from one location to another, feeding materials into a machine for processing, retrieving materials from a machine for processing, handling of raw materials by

transporting them to another location for processing, cutting down trees and other vegetation, and similar tasks are all accomplished with the help of such machines (Figures 4.14 and 4.15).

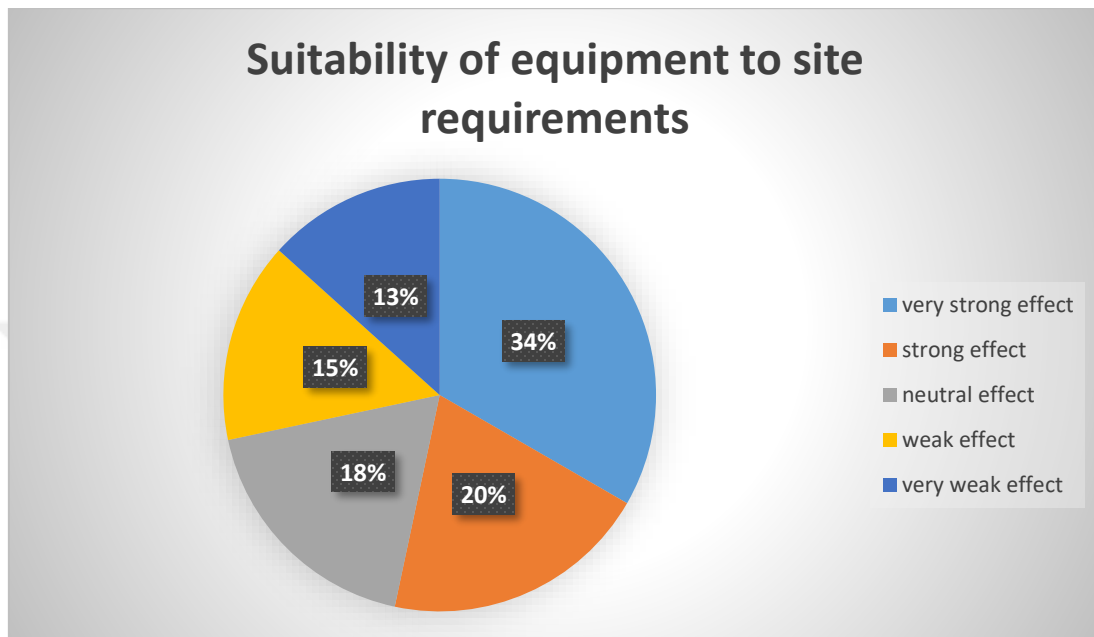


Figure 4.14: Suitability of equipment to site requirements factor effect on quantity per floor.

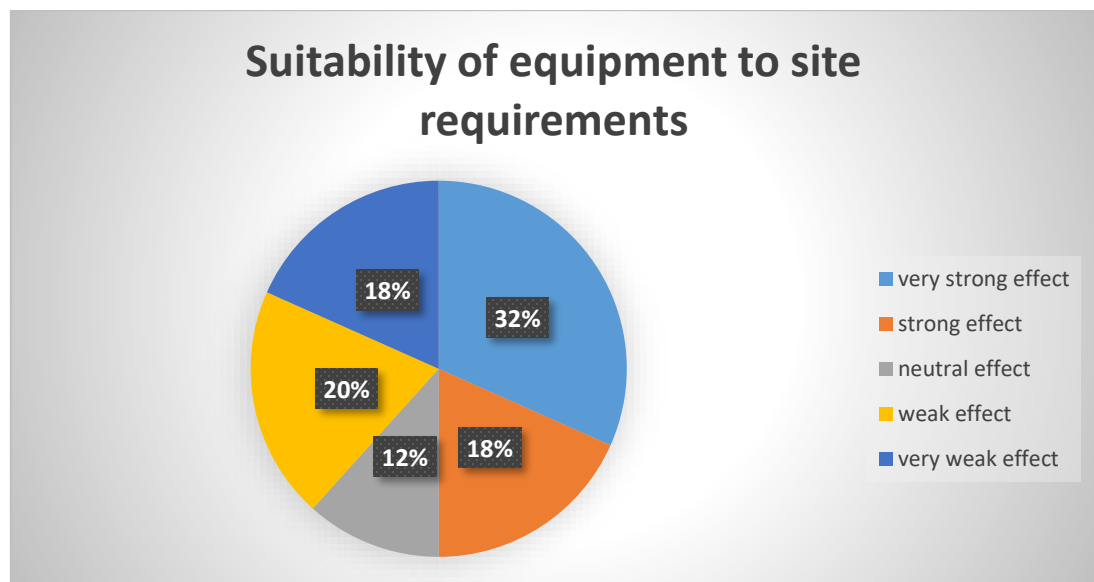


Figure 4.15: Suitability of equipment to site requirements factor effect on Floor height.

Any action taken to ensure that a company's machinery continues to function reliably is considered equipment maintenance. Both preventative maintenance and emergency repairs could fall under this category. Mechanical assets, tools, big off-road vehicles, and computers are all examples of equipment. According to the survey's findings, this variable is between 24% and 43% as important in terms of quantity per floor and floor heights. Preventing health and safety issues and environmental damage, increasing asset life with fewer breakdowns and downtime, decreasing operating costs, increasing productivity and profitability, and improving quality of life are all possible thanks to a well-implemented maintenance management system and a knowledgeable and capable maintenance and operation staff. The phrase "Operation" is often used interchangeably with "Maintenance," but what does each term actually mean? Operation refers to the provision of materials and energy, as well as the performance of labor, necessary to keep an asset operating smoothly on a day-to-day basis. And maintenance is the work done on an asset to keep it in as close to original condition as possible, to realize its normal life expectancy, to stop a device or component of an asset from failing, or to fix the normal equipment degradation experienced by the device as it is used to keep it in good working order. An effective maintenance management system will guarantee a smooth building process and a high-quality end result. It can help avoid issues and save money and time in the long term. Maintenance management software that delivers the desired results will be developed in accordance with the requirements of the construction project at hand and will undergo frequent evaluation and updating. It needs to be crafted such that the project complies with all applicable laws, regulations, and contracts. Studies on the dependability of machinery have shown that the frequency with which it is tampered with directly correlates with the frequency with which it breaks down. Every time a piece of equipment is serviced, there is a greater probability that something will go wrong. The likelihood of an error occurring increases with each disruption that occurs, even if it doesn't occur the first two times. Standing on the ground and staring up at a motor or drive at the top of a bucket elevator or dust collector with no means to access it is the most aggravating thing a maintenance worker can do. He is more concerned with the safety of his ascent and job atop the apparatus. In the absence of secure access during construction, maintenance workers can take one of three actions. They'll set up permanent access on their own anyway. Alternately, they might erect

some makeshift scaffolding that gets taken down once the work is done. Scaffolding is expensive to hire and erect and will eventually cost more than building a permanent structure. Or they'll avoid the trouble and waste time of setting up safe access by taking an unjustified risk (Figures 4.16 and 4.17).

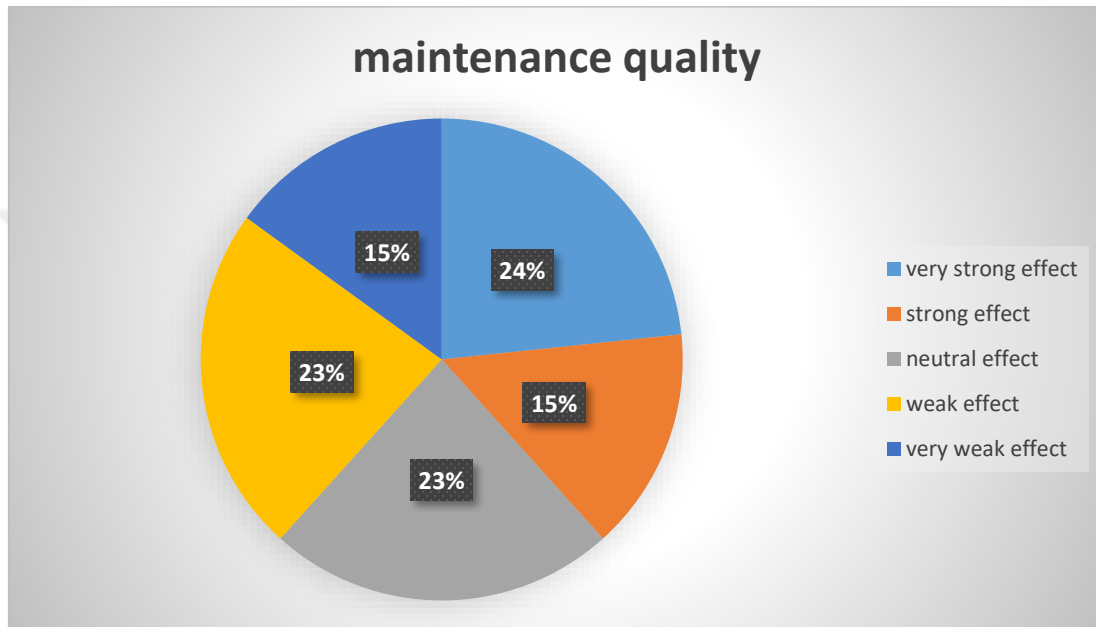


Figure 4.16: Maintenance quality factor effect on quantity per floor.

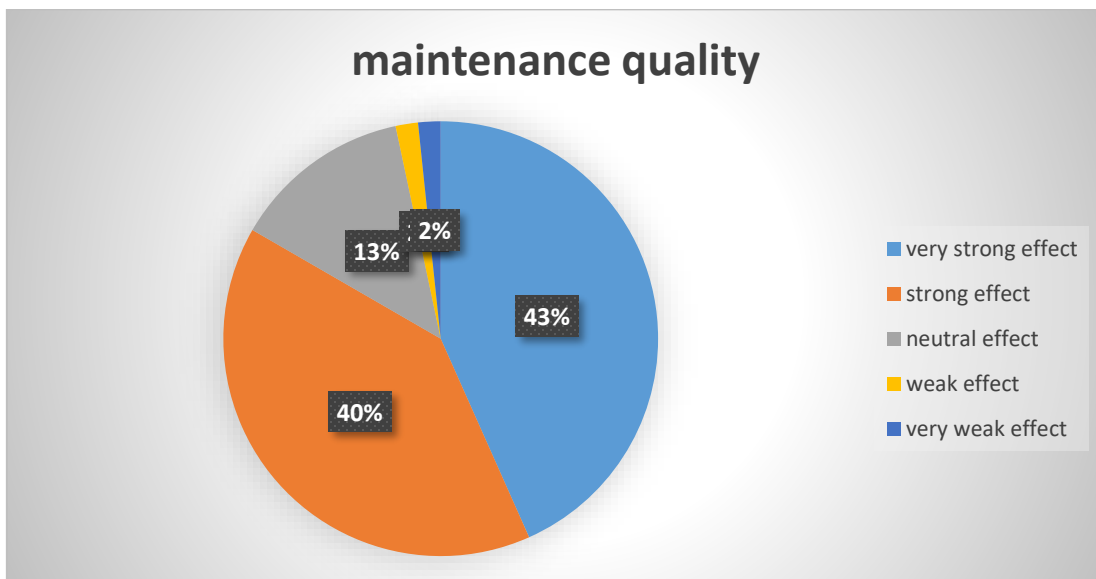


Figure 4.17: Maintenance quality factor effect on Floor height.

4.5 EFFICIENT SVM RESULTS

SVM analysis is a helpful method for prioritizing indicators evaluated on Likert-type scales and for determining which criteria are most important based on participant replies. A relative index analysis was used to rank the criteria in order of importance. Tables in the following sections display the rankings achieved for each criterion by employing the relative index analysis. Based on these rankings, eight factors were shown to have significant impacts on project cost estimates. Table (4.4) presents the SVM results which ranks the effect of each factor on construction cost

Table 4.4: SVM results of ranking factors.

Itam	SVM Frequency Results	SVM Relative Frequency	Factor Score
Work scheduling method	37.74	11.32%	0.68
number of supervisors	37.34	11.20%	0.67
workers experience	45.73	13.72%	0.83
Change job tasks	39.66	11.90%	0.72
Number of equipment available	37.74	11.32%	0.68
Quality of equipment available	42.24	12.67%	0.76
maintenance quality	37.48	11.24%	0.68
Suitability of equipment to site requirements	55.42	16.63%	1.00

The results observed that the suitability of equipment to site requirements is the most important factor. it controls all the other factors such as number of equipment available,

quality of equipment available and maintenance quality. and effect on the work scheduling method, number of supervisors and workers experience (Figure 4.18).

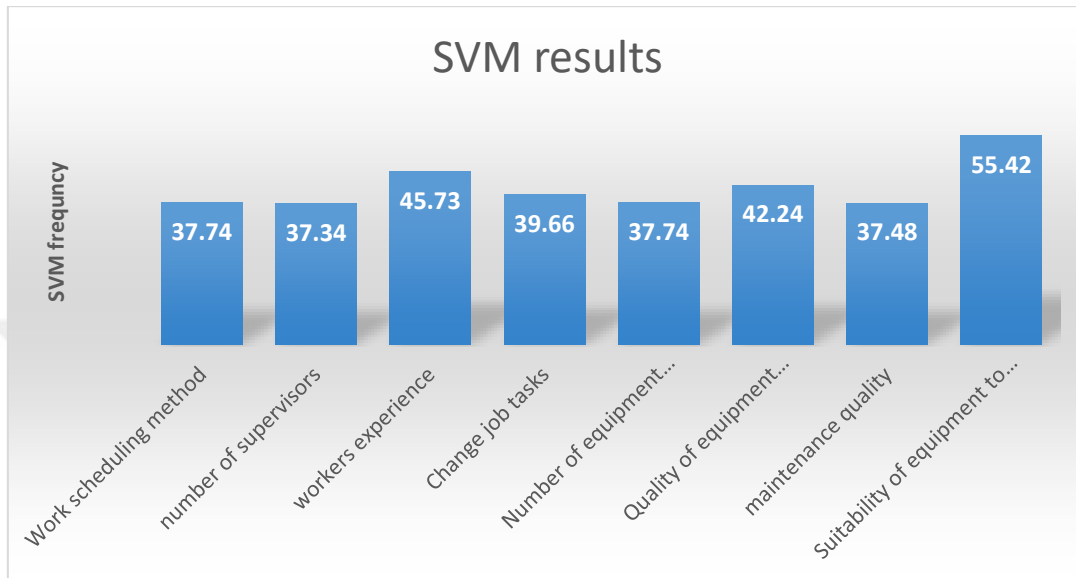


Figure 4.18: Results of SVM ranking factors.

4.5.1 Proposed Model Validation

In this part, the proposed model based on the LS-SVM with a cross-validation approach is applied to the available dataset based on the real data reported in [74] to assess its efficacy. Site studies and the owner's preliminary needs can be divided into two primary categories. Table (4.5) shows 32 input patterns and 8 for simulated validation situations.

The conceptual phase of a construction project's cost is affected by 10 elements as: (1) Site area (in square meters); (2) Geology property; (3) Influencing householder number; (4) Earthquake impact; (5) Planning householder number; (6) Total floor area (in square meters); (7) Floor over ground (in stories); (8) Floor underground (in stories); (9) Decoration class; (10) Facility class; and (11) Normalized cost of the building project.

The cost of building projects was in American Dollar per square meter. In Table 1, factors 1, 3, 5, 6, 7, and 8 are quantitative, whereas factors 2, 4, 9, and 10 are qualitative.

In Table (4.6), the qualitative characteristics are outlined. The dataset contains 80 rows of data, of which 20 rows are chosen to evaluate the suggested intelligent model as well as two well-known methods, namely Nonlinear Regression (NR) and Evolutionary Fuzzy Neural Interface Model (EFNIM). The sequential data is then used by the model as training data. In the training phase, a cross-validation approach is used to address the issues caused by the short training dataset.

Table 4.5: Patterns for conceptual estimation of building cost.

Input patterns												
No.	Building cost	Input										Output
		1	2	3	4	5	6	7	8	9	10	
1	434,769.239	909.3438	1	38	1	60	7137.7	14	2	1	2	0.643458
2	475,998.701	1715.448	2	2	1	29	6848.01	15	1	3	1	0.704478
3	657,065.310	2259.313	1	20	1	16	6934.26	19	3	1	2	0.972457
4	414,989.789	1851.813	1	120	1	95	9238.73	10	2	2	2	0.614185
5	620,201.583	2989.521	1	44	1	175	19275.83	12	2	1	3	0.917898
6	662,232.914	3913.427	2	18	1	104	6629.14	14	2	3	3	0.980105
7	379,573.882	3144.719	1	23	1	241	24185.31	22	2	2	2	0.561769
8	314,711.542	927.7292	1	124	1	14	10606.56	16	3	1	1	0.465773
9	270,720.085	6019.646	1	147	1	272	43767.47	19	3	1	1	0.400666
10	491,590.610	2982.083	1	12	1	94	16934.4	16	2	2	3	0.727554
11	376,566.872	1928.323	2	0	1	218	13233.82	19	3	2	2	0.557319
12	331,083.046	2238.24	2	33	1	55	17399	19	2	2	1	0.490003
13	273,682.547	3360.313	2	78	1	154	17667.02	12	2	1	1	0.40505

Table 4.5: Patterns for conceptual estimation of building cost. “tables continued”

14	420,847.893	2902.823	1	22	1	160	36542.68	33	4	2	2	0.622855
15	437,219.397	867.75	1	175	1	151	8638.9	19	3	2	2	0.647085
16	426,572.350	1370.49	3	224	1	12	7665.56	8	2	3	2	0.631327
17	570,240.653	2397.938	1	88	1	70	20517.38	19	3	3	3	0.843956
18	534,067.424	840.6146	1	45	1	86	8727.04	19	3	3	3	0.79042
19	603,250.951	4557.667	2	12	1	59	15588.21	15	2	3	3	0.892811
20	327,719.649	822.9792	1	0	1	38	6190.73	16	2	2	1	0.485025
21	547,921.949	1619.24	2	125	1	233	13191.88	16	2	3	3	0.810924
22	477,335.151	2896.927	1	29	1	68	6629.14	14	1	2	2	0.706456
23	461,119.566	7924.792	1	78	1	283	28735.09	23	3	1	2	0.682457
24	515,446.230	1968.719	1	74	1	235	12098.87	18	2	3	3	0.76286
25	273,838.467	3042.625	1	147	1	161	17222.73	11	2	1	1	0.405281
26	271,343.761	1415.594	1	23	1	96	9051.38	12	2	1	1	0.401589
27	563,202.020	1821.75	1	36	1	103	15263.04	16	2	3	3	0.833539
28	504,643.265	2412.438	2	124	1	100	13371.74	15	2	1	3	0.746872
29	356,742.873	3278.052	2	78	1	173	20768.76	12	2	1	2	0.527979
30	505,266.941	1828.01	1	21	1	106	23942.59	19	2	1	2	0.747795
31	415,346.176	2560.063	2	63	1	89	2393.2	23	2	1	3	0.614712
32	587,748.139	3487.479	1	77	1	154	28498.2	12	1	1	2	0.869867
33	442,676.565	3840.885	1	82	1	115	8773.19	10	1	3	1	0.655161
34	448,735.135	2962.875	1	64	1	40	13616.38	18	3	3	2	0.664128

Table 4.5: Patterns for conceptual estimation of building cost. “tables continued”

35	302,438.482	1941.635	3	29	1	90	2832.2	23	2	2	1	0.447609
36	398,596.011	3278.052	2	33	1	152	23840.39	14	3	1	1	0.589922
37	437,375.316	2963.188	1	47	1	89	27368.39	10	1	2	2	0.647315
38	398,596.011	3557.167	1	86	1	118	25145.72	15	2	3	1	0.589922
39	547,120.079	2015.969	2	98	1	82	6087.76	23	1	2	3	0.809738
40	484,663.347	2788.802	1	122	1	151	13719.02	22	2	1	2	0.717302

Table 4.6: Description of qualitative factors for conceptual cost estimating.

Influencing factor	Qualitative option	Value
Geology property	Soft	1
	Medium	2
	Hard	3
Earthquake impact	Low	1
	High	2
Decoration class	Basic type	1
	Normal type	2
	Luxurious type	3
Facility class	Basic type	1
	Normal type	2
	Luxurious type	3

Sequential data represents the indicated qualities, and training data are normalized into a (0, 1) range to prevent numerical issues and attributes with larger numeric ranges from predominating those with lower numeric ranges. To normalize data, use function (7). The performance of the suggested model is assessed using three indices; mean absolute average error (MAPE), mean square error (MSE), and R-squared (R^2), as indicated by Equations (4.1 - 4.3):

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (4.1)$$

$$MSE = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (4.2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (4.3)$$

where, y_i and $\hat{y}_i$ represent the actual and estimated values of the i-th data, respectively. $\bar{y}$ is the average of actual data and N is the number of data. The overall comparative results based on the $MAPE$, MSE and R^2 indices are illustrated for the proposed model and two famous techniques in Table (4.7).

$MAPE$ and MSE often reflect accuracy as a percentage in statistics. According to this model, $MAPE = 0.625$ for LS-SVM, 2.214 for EFNIM, and 3.935 for NL indicating that the LS-SVM has a lower and greater percentage error than EFNIM and NR, respectively. The wide applicability of the prediction model is measured by the coefficient of determination R^2 , which quantifies how well data points fit a curve or a line. When represented as a percentage, R^2 computes how much of the variance in the output response can be attributed to the model's predictors. R^2 values fall within the range [0,1]. As shown in Figure (4.19), the value $R^2 = 0.9147$ for our cleverly developed model may be understood as follows: about 91% of the variation in the response is attributable to the selected predictors, and the remaining 9% is related to unknown variability.

Here, it is important to emphasize that since various types of predictive models may be appropriate depending on the type of relationship between the predictors and the dependent

variable, it is best to test them all out to find the one that best fits our data and provides the most accurate predictions. The authors confirmed that the cross-validation approach was well suited for trustworthy estimation after obtaining pleasing results with LS-SVM with an error of less than 9%.

As shown in Figure (4.20), the prediction made using the suggested model yields results that are adequate. The minimum three indices in the final prediction results of the suggested model show strong performance and adaptability to the conceptual building cost in the construction sector. Project managers may assess construction projects appropriately, particularly in feasibility studies, by utilizing the suggested model. Additionally, it raises the likelihood that building projects will be successful.

Table 4.7: Overall comparative results.

Intelligent techniques	MAPE	MSE	R ²
Proposed model	0.625	0.1687	0.9147
EFNIM	2.214	0.3187	0.6687
NR	3.935	0.4987	0.5214

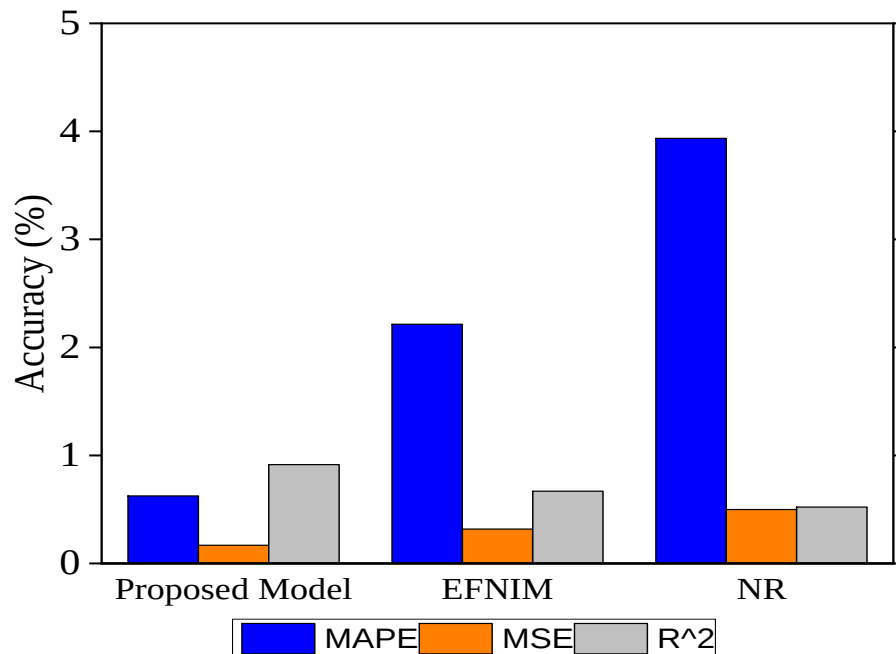


Figure 4.19: Comparison of accuracy for proposed model, EFNIM, and NL cost estimation models.

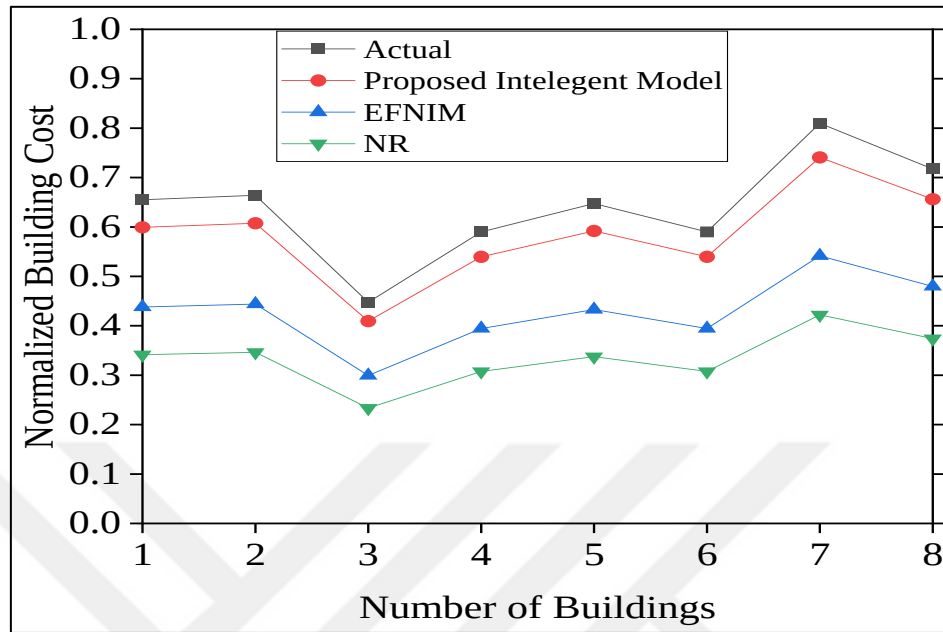


Figure 4.20: Pictorial representations of the proposed model and other two famous techniques.

4.5.2 Results of Cost Estimation Process

The primary goal of construction drawings is to accurately depict the finished product prior to its assembly. Whenever feasible, confusion and doubt should be avoided by using clear and well-coordinated construction drawings. Correctly organizing the designs helps reduce delays and confusion. The materials, concepts, techniques, etc., that are required to perform the works will be outlined in the specifications. The construction drawings provide a visual representation, showing the order of components, dimensions, and other pertinent information. It's possible that they'll repeat some of the information found in the specifics, but it's best to avoid doing that whenever possible by pointing readers in the direction of the relevant decisions instead. For that, the Revit drawing results observe all the quantities and dimensions. Figure (4.21) presents the building case study of ten floors with area of 420m^2 . The cost calculation presented in Table (4.8).

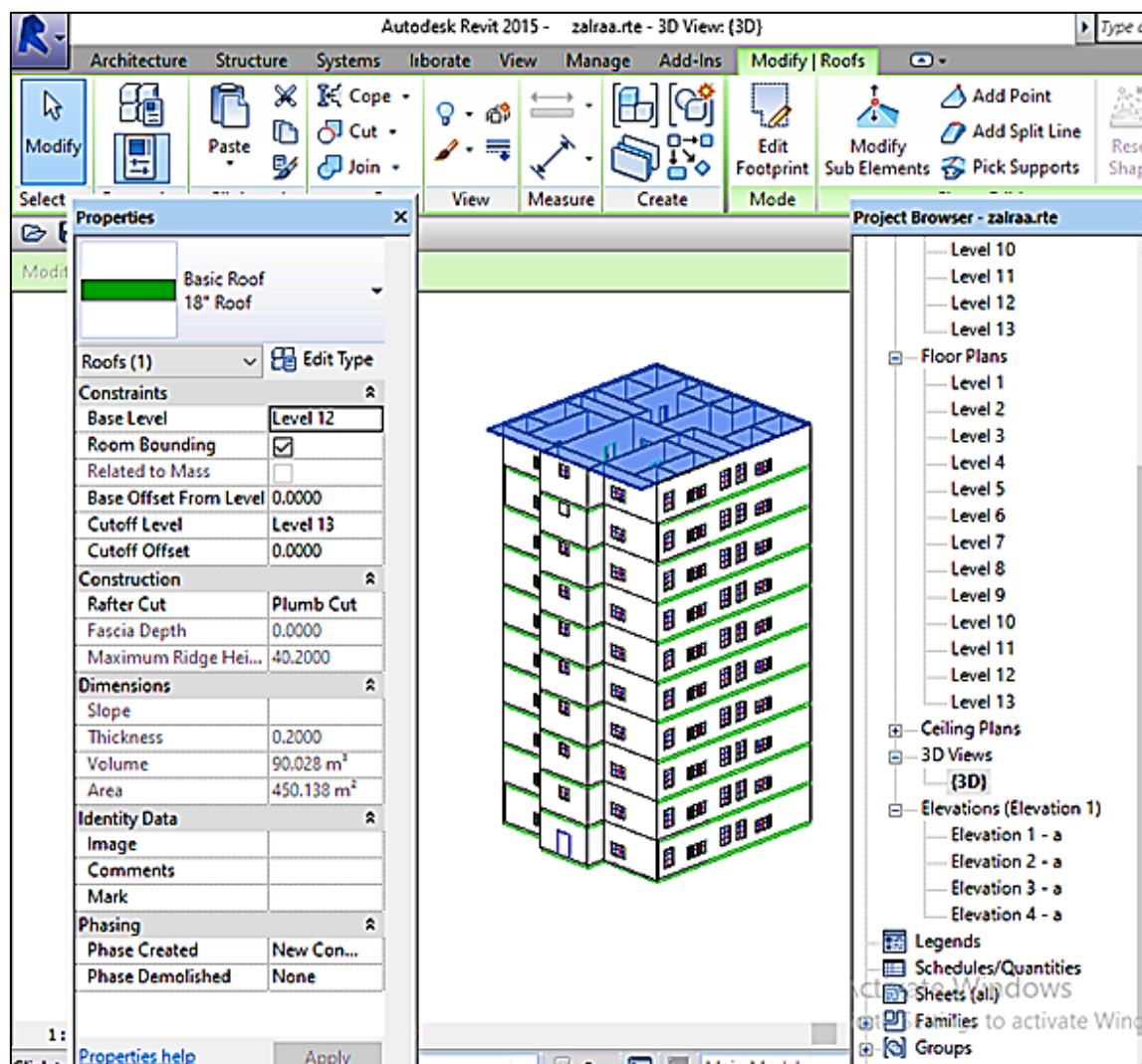


Figure 4.21: The case study cost estimation.

Table 4.8: Cost estimation of the case study.

Revit quantities results	Area of first case	conventional unit price USD	conventional total price USD
Wall quantities	16329.1	180	2939238
Floor quantities	4208.2	375	1578075

When applying the SVM score factors results on the building cost, the results observe a overrun in cost as in Figures (4.22 and 4.23). The results can present the overrun values in USD if the project manager ignores these factors.

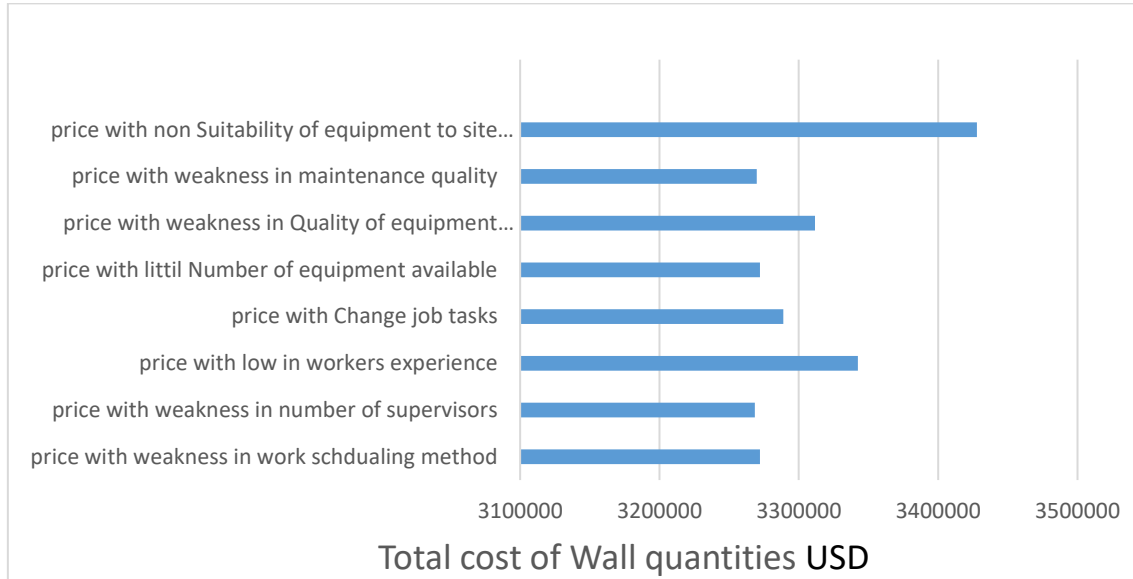


Figure 4.22: The differences in walls construction cost USD (\$) under factors effect.

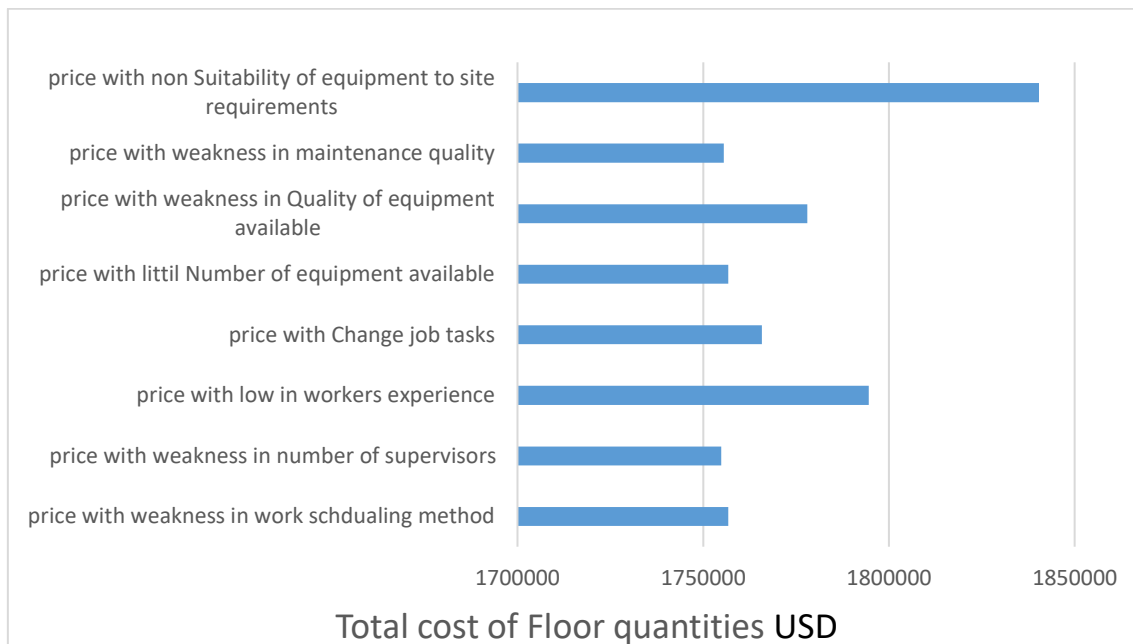


Figure 4.23: The differences in floor construction cost USD (\$) under factors effect.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 GENERAL

This chapter provides conclusions based on the findings of this research. Recommendations are also provided for future research on this subject matter.

5.2 CONCLUSIONS

The aim of this research is to provide an efficient approach and accurate model for estimating the building cost arising from construction project factors in Iraq by creating a computational model that may help the parties involved in construction projects in obtaining the obstacles in the early stages of the project. A novel intelligent model based on cross-validation and support vector machine approaches was suggested in this research. With the help of the proposed model, the LS-SVM was given a stronger ability to generalize the input-output connection it had learned throughout its training phase to make accurate predictions for brand-new input data. The Evolutionary Fuzzy Neural Interface Model and Nonlinear Regression were put up against the suggested model for a conceptual cost estimate of construction projects. It was determined through comparison that the cross-validation approach was suitable for accurate estimation. Using the data from the building projects, the suggested model exhibited improved generalization performance and produced lower estimation errors. The conclusions that can be revealed as a result of conducting survey and modeling investigations can be presented as:

- a. Effective systems for scheduling work are essential since, without them, tasks cannot be completed on schedule or to the required quality. Despite being evaluated as highly strong by 45% of respondents, this is likely due to bad management, inadequate job scheduling, and subsequent delayed output.
- b. A supervisor's "span of control" is the number of workers under their supervision. This relates to the manager's capacity to effectively oversee a given number of employees. Having one manager responsible for too many employees is a common source of conflict in the business world, making the concept of "span of control" essential.

- c. The whole of a worker's experiences during their time on a construction project is given 23% of weight.
- d. The cost of overtime is affected by several variables, including the duration of the work, the availability of workers in the area, the decisions made by management, and the location of the project.
- e. Poor management, which includes factors like inadequate provision of tools leading to inefficient use, the use of outdated and obsolete equipment, and a lack of replacement parts, is a major contributor to problem number five, which was regarded as having a very strong effect by 40% of respondents.
- f. 24 percent of specialists and consulting engineers consider the fact that schedules must be applied manually by project managers to be a critical factor. These procedures required processing huge amounts of information, which is impossible for a single human brain to remember and organize without some form of external aid.
- g. It is essential that the machinery be suitable for the needs of the place. Approximately one-third of professionals (34%) agree that it is crucial. When the proper equipment is used, work can be completed rapidly, effectively, and with minimal risk to the workers.
- h. According to the SVM findings, equipment that is well-suited to the needs of the site is the most crucial consideration. It regulates all the other aspects, like the quantity and quality of available equipment and the standard of its upkeep. Its impact on scheduling approach, supervisor count, and employee background.
- i. The results of $MAPE=0.625$, $MSE=0.1687$, and $R^2=0.9147$ (91.5%) demonstrate the high predictive capabilities of the suggested LS-SVM.
- j. The values of the input parameters can have an impact on how well the suggested intelligent model for conceptual cost estimate performs.

5.3 RECOMMENDATIONS FOR FUTURE STUDIES

As an extension of this research, optimizing the suggested model is suggested to increase yields and overcome some of the challenges. Also, results from the most recent study were encouraging, and this technology is expected to continue making major strides, especially in the field of infrastructure engineering. However, in addition to future research, it is important

to provide the following suggestions to decision-makers in the project implementation sector in light of the findings of this study:

First, there needs to be a heightened focus on budgetary considerations and data utilization by all stakeholders involved in building projects.

Second, it is recommended that there be a database of cost factors and that systematic research be conducted.



REFERENCES

- [1] M. Y. Cheng, H. C. Tsai, and E. Sudjono, "Conceptual cost estimates using evolutionary fuzzy hybrid neural network for projects in construction industry". *Expert Systems with Applications*, 2010- 37, 4224–4231.
- [2] M. Y. Cheng and Y. W. Wu, "Construction conceptual cost estimates using support vector machine," 22nd Int. Symp. on Automation and Robotics in Construction (ISARC 2005), Ferrara (Italy).
- [3] A. Leśniak and K. Zima, "Cost calculation of construction projects including sustainability factors using the Case Based Reasoning (CBR) method," *Sustain.*, vol. 10, no. 5, 2018, doi: 10.3390/su10051608.
- [4] W. Alfaggi and S. Naimi, "An Optimal Cost Estimation Practices of Fuzzy AHP for Building Construction Projects in Libya," vol. 8, no. 06, pp. 1194–1204, 2022.
- [5] M. Reihanifar, S. Naimi, "Proje ve Maliyet Yonetimi Yontemleriyle Kalitenin ve Verimliligin Artirilmasinin Incelenmesi," *Istanbul Aydin Univ. Derg.*, vol. 8, no. 29, pp. 51–65, 2016, doi: 10.17932/iau.iaud.m.13091352.2016.8/29.51-65.
- [6] A. Z. Sampaio, "Introduction of BIM methodology in education: Concept and application," pp. 19–27, 2018, doi: 10.4995/head18.2018.7443.
- [7] M. Celikag and S. Naimi, "Building construction in North Cyprus: Problems and alternatives solutions," *Procedia Eng.*, vol. 14, no. December 2011, pp. 2269–2275, 2011, doi: 10.1016/j.proeng.2011.07.286.
- [8] A. Ramírez-Valenzuela, G. G. Gamarra-Díaz, and A. A. Erazo-Rondinel, "Proposal Model for the Management of Construction Based on Flows - a Complex Adaptive System," *IGLC 2021 - 29th Annu. Conf. Int. Gr. Lean Constr. - Lean Constr. Cris. Times Responding to Post-Pandemic AEC Ind. Challenges*, pp. 859–869, 2021, doi: 10.24928/2021/0205.
- [9] A. K. M. Patil and E. M. S. ra. Patil, "Sustainable Construction Materials & Technology in Context with Sustainable Development," *Int. J. Eng. Res. Technol.*, vol. 10, no. 1, pp. 112–117, 2017, [Online]. Available: <http://www.irphouse.com>.
- [10] P. Kaur, "Artificial Neural Networks As an Effective Project Management Tool," vol. 4, pp. 229–239, 2016.

- [11] T. R. Committee, A. Rashidi, and I. P. Fulfillment, "Evaluating the Performance of Machine-Learning Techniques for Recognizing Construction Materials in Digital Images Evaluating the Performance of Machine-Learning Techniques for Recognizing Construction," no. August, 2013.
- [12] S. Tayefeh Hashemi, O. M. Ebadati, and H. Kaur, "Cost estimation and prediction in construction projects: a systematic review on machine learning techniques," *SN Appl. Sci.*, vol. 2, no. 10, pp. 1–27, 2020, doi: 10.1007/s42452-020-03497-1.
- [13] IPA, "Cost Estimating Guidance. A best practice approach for infrastructure projects and programmes," 2021.
- [14] M. K. Othman, "Cost Estimation," vol. 4, no. January, 2004, doi: 10.13140/RG.2.1.3734.0244.
- [15] J. Bates *et al.*, "Recommended practice (draft): Cost estimate classification system as applied in engineering, procurement, and construction for the process industries," *Cost Eng. (Morgantown, West Virginia)*, vol. 39, no. 4, pp. 15–21, 2005.
- [16] NJDOT, "Cost Estimating Guideline," *Progr. Manag. Off.*, p. 126, 2016.
- [17] M. Al-Siyabi, A. Alnuaimi, M. Khadem, and K. Alzebdeh, "Cost estimation practices prevalent in construction projects in Oman," *J. Eng. Res.*, vol. 16, no. 2, pp. 115–129, 2019, doi: 10.24200/tjer.vol16iss2pp115-129.
- [18] A. H. Ibrahim and L. M. Elshwafy, "Factors affecting the accuracy of construction project cost estimation in Egypt," *Jordan J. Civ. Eng.*, vol. 15, no. 3, pp. 329–344, 2021.
- [19] M. Aslam, E. Baffoe-Twum, and F. Saleem, "Design Changes in Construction Projects – Causes and Impact on the Cost," *Civ. Eng. J.*, vol. 5, no. 7, pp. 1647–1655, 2019, doi: 10.28991/cej-2019-03091360.
- [20] D. Przywara and A. Rak, "Analysis construction industry on the basis of price trends of labor cost," *MATEC Web Conf.*, vol. 174, pp. 1–7, 2018, doi: 10.1051/matecconf/201817404005.
- [21] P. Fox and M. Skitmore, "Factors facilitating construction industry development," *Build. Res. Inf.*, vol. 35, no. 2, pp. 178–188, 2007, doi: 10.1080/09613210600980192.
- [22] S. Oparin, N. Chepachenko, and M. Yudenko, "Problems in Forming Cost Estimates for Construction Industry," *CBU Int. Conf. Proc.*, vol. 4, pp. 179–186, 2016, doi: 10.12955/cbup.v4.759.

- [23] F. Arif, S. H. Lodi, and N. Azhar, "Factors influencing accuracy of construction project cost estimates in Pakistan: Perception and reality," *Int. J. Constr. Manag.*, vol. 15, no. 1, pp. 59–70, 2015, doi: 10.1080/15623599.2015.1012141.
- [24] J. Smetanková, P. Mésároš, and K. Krajníková, "Innovative cost estimation methods for building production," *Sel. Sci. Pap. - J. Civ. Eng.*, vol. 16, no. 2, pp. 7–23, 2021, doi: 10.2478/sspjce-2021-0013.
- [25] A. A. Serbanoiu, *Construction Cost Estimate Worksheet*, no. December 2020. 2021.
- [26] M. Gołaszewska and M. Salamak, "Challenges in takeoffs and cost estimating in the BIM technology, based on the example of a road bridge model," *Czas. Tech.*, vol. 4/2017, no. August, 2017, doi: 10.4467/2353737xct.17.048.6359.
- [27] C. I. B. Joint and I. Symposium, "CONSTRUCTION FACING WORLDWIDE CHALLENGES," pp. 27–30, 2009.
- [28] A. Challal and M. Tkiouat, "The Design of Cost Estimating Model of Construction Project: Application and Simulation," *Open J. Account.*, vol. 01, no. 01, pp. 15–26, 2012, doi: 10.4236/ojacct.2012.11003.
- [29] K. H. Hyari, A. Al-Daraiseh, and M. El-Mashaleh, "Conceptual Cost Estimation Model for Engineering Services in Public Construction Projects," *J. Manag. Eng.*, vol. 32, no. 1, 2016, doi: 10.1061/(asce)me.1943-5479.0000381.
- [30] S. Woo, Y. Jung, Y. Lee, and B.-N. Lee, "Approximate Cost Estimating System for Construction of Steel Mill," *18th IAARC/CIB/IEEE/IFAC Int. Symp. Autom. Robot. Constr.*, no. September 2001, 2017, doi: 10.22260/isarc2001/0021.
- [31] N. A. Adillah Ismail, E. Utiome, R. Owen, and R. Drogemuller, "Exploring Accuracy Factors in Cost Estimating Practice towards Implementing Building Information Modelling (BIM)," no. January, pp. 364–373, 2015, doi: 10.32738/ceppm.201509.0036.
- [32] F. Fanny, "A Simple Method for Cost Estimating and Controlling," *Int. J. New Media Technol.*, vol. 5, no. 2, pp. 58–61, 2019, doi: 10.31937/ijnmt.v5i2.833.
- [33] A. C. Yu Hao *et al.*, "Cost estimation methods for internet infrastructure deployment in Rural Sarawak: a review," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 19, no. 3, pp. 1375–1383, 2020, doi: 10.11591/ijeecs.v19.i3.pp1375-1383.
- [34] S. Mirdamadi, A. Etienne, A. Hassan, J. Y. Dantan, and A. Siadat, "Cost estimation method for variation management," *Procedia CIRP*, vol. 10, pp. 44–53, 2013, doi:

10.1016/j.procir.2013.08.011.

- [35] C. Rush and R. Roy, "Expert judgement in cost estimating: Modelling the reasoning process," *Concurr. Eng. Res. Appl.*, vol. 9, no. 4, pp. 271–285, 2001, doi: 10.1177/1063293x0100900404.
- [36] P. Matejka and S. Vitasek, "Comparison of different cost estimation methods with use of building information modelling (BIM)," *Eng. Rural Dev.*, vol. 17, no. October 2021, pp. 843–849, 2018, doi: 10.22616/ERDev2018.17.N154.
- [37] Z. Vojinovic and V. Kecman, "Modelling empirical data to support project cost estimating: Neural networks versus traditional methods," *Constr. Innov.*, vol. 1, no. 4, pp. 227–243, 2001, doi: 10.1108/14714170110814622.
- [38] X. X. Huang, L. B. Newnes, and G. C. Parry, "The adaptation of product cost estimation techniques to estimate the cost of service," *Int. J. Comput. Integr. Manuf.*, vol. 25, no. 4–5, pp. 417–431, 2012, doi: 10.1080/0951192X.2011.596281.
- [39] W. Daniel, "Improved modeling of three-point estimates for decision making : going beyond the triangle NAVAL POSTGRADUATE," 2016.
- [40] I. Ochei, "Cost Systems, Cost Allocation, Planning and Decision Making, Cost Planning for the Product Life Cycle and Operational Performance Measurement," *Work. costing Authors*, no. November, 2014, doi: 10.13140/2.1.3778.7843.
- [41] M. A. Salunkhe, "Comparative Analysis of Construction Cost Estimation Model Using SVM and Regression Analysis GIS SCIENCE JOURNAL ISSN NO : 1869-9391 Comparative Analysis of Construction Cost Estimation Model Using SVM and Regression Analysis," no. July, 2020.
- [42] P. A. Zhao and C. C. Wang, "A Comparison of Using Traditional Cost Estimating Software and BIM for Construction Cost Control," *ICCREM 2014 Smart Constr. Manag. Context New Technol. - Proc. 2014 Int. Conf. Constr. Real Estate Manag.*, no. November, pp. 256–264, 2014, doi: 10.1061/9780784413777.031.
- [43] S. Ekung, A. Lashinde, and E. Adu, "Critical Risks to Construction Cost Estimation," *J. Eng. Proj. Prod. Manag.*, vol. 11, no. 1, pp. 19–29, 2021, doi: 10.2478/jeppm-2021-0003.
- [44] D. Cooper, D. MacDonald, and C. Chapman, "Risk analysis of a construction cost estimate," *Int. J. Proj. Manag.*, vol. 3, no. 3, pp. 141–149, 1985, doi: 10.1016/0263-

7863(85)90065-1.

- [45] M. Abazid and H. Harb, "An Overview of Risk Management in The Construction Projects," *Acad. Res. Int.*, vol. 9, no. 2, pp. 73–79, 2018.
- [46] H. Eliufoo, "Risk Factors in Cost Estimation: Building Contractors' Experience," *Am. J. Civ. Eng. Archit.*, vol. 6, no. 3, pp. 123–128, 2018, doi: 10.12691/ajcea-6-3-5.
- [47] J. Zuo and N. Chileshe, "Risk management in civil construction projects – From cost estimating perspective RISK MANAGEMENT IN CIVIL CONSTRUCTION PROJECTS – FROM COST ESTIMATING PERSPECTIVE," no. September 2014, 2011.
- [48] S. P., "Predicting Construction Project Duration With Support Vector Machine," *Int. J. Res. Eng. Technol.*, vol. 02, no. 11, pp. 12–24, 2013, doi: 10.15623/ijret.2013.0211003.
- [49] V. B. Chandanshive and A. R. Kambekar, "Prediction of Building Construction Project Cost Using Support Vector Machine," *Ind. Eng. Strateg. Manag.*, vol. 1, pp. 31–42, 2021.
- [50] S. Petrusheva, D. Car-Pušić, and V. Zileska-Pancovska, "Support Vector Machine Based Hybrid Model for Prediction of Road Structures Construction Costs," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 222, no. 1, 2019, doi: 10.1088/1755-1315/222/1/012010.
- [51] M. Xu, B. Xu, L. Zhou, and L. Wu, "Construction Project Cost Prediction Based on Genetic Algorithm and Least Squares Support Vector Machine," no. Iccet, pp. 1004–1009, 2015, doi: 10.2991/iccet-15.2015.190.
- [52] F. K. Jaber, F. M. S. Al-Zwainy, and S. W. Hachem, "Optimizing of predictive performance for construction projects utilizing support vector machine technique," *Cogent Eng.*, vol. 6, no. 1, 2019, doi: 10.1080/23311916.2019.1685860.
- [53] A. Sung-Hoon, P. U-Yeol, K. Kyung-In, C. Moon-Young, and C. Hun-Hee, "Application of Support Vector Machines in Assessing Conceptual Cost Estimates.," *J. Comput. Civ. Eng.*, vol. 21, no. 4, pp. 259–264, 2007.
- [54] X. Zhang, J. Song, and C. Zha, "A whole process cost prediction system for construction projects based on improved support vector machines," *Int. J. Circuits, Syst. Signal Process.*, vol. 16, pp. 278–286, 2022, doi: 10.46300/9106.2022.16.34.
- [55] M. Y. Cheng and Y. W. Wu, "Construction conceptual cost estimates using support vector machine," *22nd Int. Symp. Autom. Robot. Constr. ISARC 2005*, pp. 1–5, 2005,

doi: 10.22260/isarc2005/0064.

- [56] M. Juszczak, “On the search of models for early cost estimates of bridges: An SVM-based approach,” *Buildings*, vol. 10, no. 1, 2020, doi: 10.3390/buildings10010002.
- [57] Y. R. Wang, C. Y. Yu, and H. H. Chan, “Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models,” *Int. J. Proj. Manag.*, vol. 30, no. 4, pp. 470–478, 2012, doi: 10.1016/j.ijproman.2011.09.002.
- [58] M. Y. Cheng, H. S. Peng, Y. W. Wu, and T. L. Chen, “Estimate at completion for construction projects using evolutionary support vector machine inference model,” *Autom. Constr.*, vol. 19, no. 5, pp. 619–629, 2010, doi: 10.1016/j.autcon.2010.02.008.
- [59] *et al.*, “Exploring Accuracy Factors in Cost Estimating Practice towards Implementing Building Information Modelling (BIM),” no. September, pp. 364–373, 2015, doi: 10.32738/ceppm.201509.0036.
- [60] J. Chimdi, S. Girma, A. Mosisa, and D. Mitiku, “ASSESSMENT OF FACTORS AFFECTING ACCURACY OF COST ESTIMATION IN PUBLIC BUILDING CONSTRUCTION PROJECTS IN WESTERN OROMIA REGION , ETHIOPIA,” vol. 11, no. 2, 2020, doi: 10.33736/jcest.2248.2020
- [61] Hsu, C. W., Chang, C. C. and Lin, C. J., (2003). A practical guide to support vector classification, Technical Report, Department of Computer Science, National Taiwan University, Taipei, Taiwan.
- [62] Sapankevych, N. I. and Sankar, R., (2009). Time series prediction using support vector machine: A survey. *IEEE Computational Intelligence Magazine*, 4 (2), 24–38.
- [63] Mousavi, S. M. and Iranmanesh, S. H., (2011). Least squares support vector machines with genetic algorithm for estimating costs in NPD projects. The IEEE International Conference on Industrial and Intelligent Information (ICIII 2011), Indonesia, 127–131.
- [64] Tavakkoli-Moghaddam, R., Mousavi, S. M., Hashemi, H., and Ghodratnama, A. (2011). Predicting the conceptual cost of construction projects:a locally linear neuro-fuzzy model. The First International Conference on Data Engineering and Internet Technology (DEIT), 398-401.

- [65] Vahdani, B., Iranmanesh, S.H., Mousavi, S.M. and Abdollahzade, M., (2011). A locally linear neuro-fuzzy model for supplier selection in cosmetics industry. *Applied Mathematical Modelling*, Article in press, DOI: 10.1016/j.apm.12.006.
- [66] Peng, K. L., Wu, C. H. and Goo, Y. J., (2004). The development of a new statistical technique for relating financial information to stock market returns. *International Journal of Management*, 21(4), 492–505.
- [67] Burges, C. J. C., (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2(2), 121–167.
- [68] Vapnik, V. N., (1999). *The Nature of Statistical Learning Theory*. Springer, London.
- [69] Huang, C.-F., (2012). A hybrid stock selection model using genetic algorithms and support vector regression. *Applied Soft Computing*, 12, 807–818.
- [70] Chen, K. Y. and Wang, C.-H., (2007). Support vector regression with genetic algorithms in forecasting tourism demand. *Tourism Management*, 28, 215–226.
- [71] Salgado, D.R. and Alonso, F.J., (2007). An approach based on current and sound signals for in-process tool wear monitoring. *International Journal of Machine Tools and Manufacture*, 47, 2140–2152.
- [72] Efron, B. and Tibshirani, R. J., (1993). *An Introduction to the Bootstrap*, London: Chapman & Hall.
- [73] Duan, K., Keerthi, S. and Poo, A., (2001). Evaluation of simple performance measures for tuning SVM hyper parameters. Technical report, Singapore: National University of Singapore, Department of Mechanical Engineering
- [74] Hsieh, W. S., (2002). Construction conceptual cost estimates using evolutionary fuzzy neural inference model. M. S. thesis, Dept. of Construction Engineering, National Taiwan University Of Science and Technology, Taiwan.
- [75] A. Khaleel, S. Naimi, “Automation of cost control process in construction project building information modeling (BIM),” *Periodicals of Engineering and Natural Sciences (PEN)*, vol. 10, no. 6, pp. 28–38, 2022

APPENDIX A: ESSENTIAL BILL OF WALL QUANTITIES.

Wall Schedule					
No.	Area (m ²)	Type	No.	Area (m ²)	Type
1	70.08	Wall 1	30	68.16	Wall 1
2	68.40	Wall 1	31	67.44	Wall 1
3	71.65	Wall 1	32	70.69	Wall 1
4	68.16	Wall 1	33	68.16	Wall 1
5	8.00	Wall 1	34	7.04	Wall 1
6	24.00	Wall 1	35	19.03	Wall 1
7	7.04	Wall 1	36	7.04	Wall 1
8	44.81	Wall 1	37	43.85	Wall 1
9	44.67	Wall 1	38	44.67	Wall 1
10	35.85	Wall 1	39	35.85	Wall 1
11	27.04	Wall 1	40	27.04	Wall 1
12	39.04	Wall 1	41	39.04	Wall 1
13	10.14	Wall 1	42	9.18	Wall 1
14	15.04	Wall 1	43	15.04	Wall 1
15	10.14	Wall 1	44	9.18	Wall 1
16	11.04	Wall 1	45	11.04	Wall 1
17	11.04	Wall 1	46	11.04	Wall 1
18	27.32	Wall 1	47	27.32	Wall 1
19	11.04	Wall 1	48	11.04	Wall 1
20	27.32	Wall 1	49	27.32	Wall 1
21	25.18	Wall 1	50	25.18	Wall 1
22	25.18	Wall 1	51	25.18	Wall 1
23	8.00	Wall 1	52	7.04	Wall 1
24	25.18	Wall 1	53	25.18	Wall 1
25	25.18	Wall 1	54	25.18	Wall 1
26	27.32	Wall 1	55	27.32	Wall 1

27	15.04	Wall 1	56	15.04	Wall 1
28	27.32	Wall 1	57	27.32	Wall 1
29	13.04	Wall 1	58	13.04	Wall 1
59	70.08	Wall 1	92	8.00	Wall 1
60	68.40	Wall 1	93	22.55	Wall 1
61	71.65	Wall 1	94	7.04	Wall 1
62	68.16	Wall 1	95	44.81	Wall 1
63	8.00	Wall 1	96	44.67	Wall 1
64	22.55	Wall 1	97	35.85	Wall 1
65	7.04	Wall 1	98	27.04	Wall 1
66	44.81	Wall 1	99	39.04	Wall 1
67	44.67	Wall 1	100	10.14	Wall 1
68	35.85	Wall 1	101	15.04	Wall 1
69	27.04	Wall 1	102	10.14	Wall 1
70	39.04	Wall 1	103	11.04	Wall 1
71	10.14	Wall 1	104	11.04	Wall 1
72	15.04	Wall 1	105	27.32	Wall 1
73	10.14	Wall 1	106	11.04	Wall 1
74	11.04	Wall 1	107	27.32	Wall 1
75	11.04	Wall 1	108	25.18	Wall 1
76	27.32	Wall 1	109	25.18	Wall 1
77	11.04	Wall 1	110	8.00	Wall 1
78	27.32	Wall 1	111	25.18	Wall 1
79	25.18	Wall 1	112	25.18	Wall 1
80	25.18	Wall 1	113	27.32	Wall 1
81	8.00	Wall 1	114	15.04	Wall 1
82	25.18	Wall 1	115	27.32	Wall 1
83	25.18	Wall 1	116	13.04	Wall 1
84	27.32	Wall 1	117	70.08	Wall 1
85	15.04	Wall 1	118	68.40	Wall 1

86	27.32	Wall 1	119	71.65	Wall 1
87	13.04	Wall 1	120	68.16	Wall 1
88	70.08	Wall 1	121	8.00	Wall 1
89	68.40	Wall 1	122	22.55	Wall 1
90	71.65	Wall 1	123	7.04	Wall 1
91	68.16	Wall 1	124	44.81	Wall 1
125	44.67	Wall 1	158	10.14	Wall 1
126	35.85	Wall 1	159	15.04	Wall 1
127	27.04	Wall 1	160	10.14	Wall 1
128	39.04	Wall 1	161	11.04	Wall 1
129	10.14	Wall 1	162	11.04	Wall 1
130	15.04	Wall 1	163	27.32	Wall 1
131	10.14	Wall 1	164	11.04	Wall 1
132	11.04	Wall 1	165	27.32	Wall 1
133	11.04	Wall 1	166	25.18	Wall 1
134	27.32	Wall 1	167	25.18	Wall 1
135	11.04	Wall 1	168	8.00	Wall 1
136	27.32	Wall 1	169	25.18	Wall 1
137	25.18	Wall 1	170	25.18	Wall 1
138	25.18	Wall 1	171	27.32	Wall 1
139	8.00	Wall 1	172	15.04	Wall 1
140	25.18	Wall 1	173	27.32	Wall 1
141	25.18	Wall 1	174	13.04	Wall 1
142	27.32	Wall 1	175	70.08	Wall 1
143	15.04	Wall 1	176	68.40	Wall 1
144	27.32	Wall 1	177	71.65	Wall 1
145	13.04	Wall 1	178	68.16	Wall 1
146	70.08	Wall 1	179	8.00	Wall 1
147	68.40	Wall 1	180	22.55	Wall 1
148	71.65	Wall 1	181	7.04	Wall 1

149	68.16	Wall 1	182	44.81	Wall 1
150	8.00	Wall 1	183	44.67	Wall 1
151	22.55	Wall 1	184	35.85	Wall 1
152	7.04	Wall 1	185	27.04	Wall 1
153	44.81	Wall 1	186	39.04	Wall 1
154	44.67	Wall 1	187	10.14	Wall 1
155	35.85	Wall 1	188	15.04	Wall 1
156	27.04	Wall 1	189	10.14	Wall 1
157	39.04	Wall 1	190	11.04	Wall 1
191	11.04	Wall 1	224	25.18	Wall 1
192	27.32	Wall 1	225	25.18	Wall 1
193	11.04	Wall 1	226	8.00	Wall 1
194	27.32	Wall 1	227	25.18	Wall 1
195	25.18	Wall 1	228	25.18	Wall 1
196	25.18	Wall 1	229	27.32	Wall 1
197	8.00	Wall 1	230	15.04	Wall 1
198	25.18	Wall 1	231	27.32	Wall 1
199	25.18	Wall 1	232	13.04	Wall 1
200	27.32	Wall 1	233	70.08	Wall 1
201	15.04	Wall 1	234	68.40	Wall 1
202	27.32	Wall 1	235	71.65	Wall 1
203	13.04	Wall 1	236	68.16	Wall 1
204	70.08	Wall 1	237	8.00	Wall 1
205	68.40	Wall 1	238	22.55	Wall 1
206	71.65	Wall 1	239	7.04	Wall 1
207	68.16	Wall 1	240	44.81	Wall 1
208	8.00	Wall 1	241	44.67	Wall 1
209	22.55	Wall 1	242	35.85	Wall 1
210	7.04	Wall 1	243	27.04	Wall 1
211	44.81	Wall 1	244	39.04	Wall 1

212	44.67	Wall 1	245	10.14	Wall 1
213	35.85	Wall 1	246	15.04	Wall 1
214	27.04	Wall 1	247	10.14	Wall 1
215	39.04	Wall 1	248	11.04	Wall 1
216	10.14	Wall 1	249	11.04	Wall 1
217	15.04	Wall 1	250	27.32	Wall 1
218	10.14	Wall 1	251	11.04	Wall 1
219	11.04	Wall 1	252	27.32	Wall 1
220	11.04	Wall 1	253	25.18	Wall 1
221	27.32	Wall 1	254	25.18	Wall 1
222	11.04	Wall 1	255	8.00	Wall 1
223	27.32	Wall 1	256	25.18	Wall 1
257	25.18	Wall 1	290	13.04	Wall 1
258	27.32	Wall 1	291	68.16	Wall 1
259	15.04	Wall 1	292	67.44	Wall 1
260	27.32	Wall 1	293	70.69	Wall 1
261	13.04	Wall 1	294	68.16	Wall 1
262	70.08	Wall 1	295	7.04	Wall 1
263	68.40	Wall 1	296	21.59	Wall 1
264	71.65	Wall 1	297	7.04	Wall 1
265	68.16	Wall 1	298	43.85	Wall 1
266	8.00	Wall 1	299	44.67	Wall 1
267	24.00	Wall 1	300	35.85	Wall 1
268	7.04	Wall 1	301	27.04	Wall 1
269	44.81	Wall 1	302	39.04	Wall 1
270	44.67	Wall 1	303	9.18	Wall 1
271	35.85	Wall 1	304	15.04	Wall 1
272	27.04	Wall 1	305	9.18	Wall 1
273	39.04	Wall 1	306	11.04	Wall 1
274	10.14	Wall 1	307	11.04	Wall 1

275	15.04	Wall 1	308	27.32	Wall 1
276	10.14	Wall 1	309	11.04	Wall 1
277	11.04	Wall 1	310	27.32	Wall 1
278	11.04	Wall 1	311	25.18	Wall 1
279	27.32	Wall 1	312	25.18	Wall 1
280	11.04	Wall 1	313	7.04	Wall 1
281	27.32	Wall 1	314	25.18	Wall 1
282	25.18	Wall 1	315	25.18	Wall 1
283	25.18	Wall 1	316	27.32	Wall 1
284	8.00	Wall 1	317	15.04	Wall 1
285	25.18	Wall 1	318	27.32	Wall 1
286	25.18	Wall 1	319	13.04	Wall 1
287	27.32	Wall 1	320	70.08	Wall 1
288	15.04	Wall 1	321	68.40	Wall 1
289	27.32	Wall 1	322	71.65	Wall 1
323	68.16	Wall 1			
324	8.00	Wall 1			
325	22.55	Wall 1			
326	7.04	Wall 1			
327	44.81	Wall 1			
328	44.67	Wall 1			
329	35.85	Wall 1			
330	27.04	Wall 1			
331	39.04	Wall 1			
332	10.14	Wall 1			
333	15.04	Wall 1			
334	10.14	Wall 1			
335	11.04	Wall 1			
336	11.04	Wall 1			
337	27.32	Wall 1			

338	11.04	Wall 1
339	27.32	Wall 1
340	25.18	Wall 1
341	25.18	Wall 1
342	8.00	Wall 1
343	25.18	Wall 1
344	25.18	Wall 1
345	27.32	Wall 1
346	15.04	Wall 1
347	27.32	Wall 1
348	13.04	Wall 1

APPENDIX B: ESSENTIAL BILL OF FLOOR QUANTITIES.

Floor Schedule			
Area	Count	Volume (m ³)	Level
420.82	1	126.25	Level 1
420.82	1	126.25	Level 1
420.82	1	126.25	Level 3
420.82	1	126.25	Level 4
420.82	1	126.25	Level 5
420.82	1	126.25	Level 6
420.82	1	126.25	Level 7
420.82	1	126.25	Level 8
420.82	1	126.25	Level 9
420.82	1	126.25	Level 10
420.82	1	126.25	Level 10
420.82	1	126.25	Level 11

APPENDIX C: ESSENTIAL BILL OF DOOR QUANTITIES.

Door Schedule 2						
Width	Type	Level	Height	Count		
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2

1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
1	THCGAB	2CE	813	Level	1	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
1	THCGAB	2CE	813	Level	3	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2

1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
1	THCGAB	2CE	813	Level	4	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
1	THCGAB	2CE	813	Level	5	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2

1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
1	THCGAB	2CE	813	Level	6	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
1	THCGAB	2CE	813	Level	7	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2

1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
1	THCGAB	2CE	813	Level	8	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
1	THCGAB	2CE	813	Level	9	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2

1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
1	THCGAB	2CE	813	Level	10	2
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	1510	x	2110mm	Sgl	Swing	Level
2	J250DR1630	2320	(1690x2370mm)	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2

1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
1	THCGAB	2CE	813	Level	11	2
2	J250DR1630	2320	(1690x2370mm)	Level	1	2

APPENDIX-D: ESSENTIAL BILL OF WINDOW QUANTITIES.

Window Schedule											
Width	Type	Mark	Head	Family	Count	Description	Family	and	Type		
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812

2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
2	1	2	Awning	2L	1	Awning	Window	Awning	-	2L:	AW1218
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	2	3	Awning	1LT	1	Awning	Window	Awning	-	1LT:	AW1812
1	3	3	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	3	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	4	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	4	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	4	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	4	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	4	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212
1	3	4	Awning	1L	1	Awning	Window	Awning	-	1L:	AW1212

APPENDIX-E: MATLAB CODE

```
clc,clear close all

%Labor productivity
%Quantity per floor
%Work scheduling method [27 26 3 3 1]
%number of supervisors [11 15 13 15 6]
%workers experience [14 11 18 9 8]
%Change task type [20 11 6 14 9]
%-----
%Floor height
%Work scheduling method [16 14 9 17 4]
%number of supervisors [23 25 10 2 0]
%workers experience [14 11 18 9 8]
%Change task type [20 11 6 14 9]
%-----

Factors_Number = [1 2 3 4 5 6 7 8]';
Questinnare_Max_Results = [43 40 36 40 39 32 46 33]';
Questionnaire_Min_Results = [5 6 16 12 5 14 9 20]';

mdl = fitlm(Factors_Number,Questinnare_Max_Results,'quadratic');
%Create predicted responses to the data.

ypred = predict(mdl,Questionnaire_Min_Results);
%Plot the original responses and the predicted responses to see how
they differ.
figure
plot(Factors_Number,Questinnare_Max_Results,'o',Factors_Number,ypred,
'r-*',Factors_Number,Questionnaire_Min_Results,'ro')
legend('Data','Predictions')
```