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LEAST SQUARE MOMENT BALANCED MACHINE: A NEW APPROACH TO ESTIMATING COST TO COMPLETION FOR CONSTRUCTION PROJECTS

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SUMMARY: *In the construction industry, traditional methods of cost estimation are inefficient and cannot reflect real-time changes. Modern techniques are essential to create new tools that outperform current cost estimation. This study introduced the Least Square Moment Balanced Machine (LSMBM), AI-based inference engine, to improve construction cost prediction accuracy. LSMBM considers moments to determine the optimal hyperplane and uses the Backpropagation Neural Network (BPNN) to assign weights to each data point. The effectiveness of LSMBM was tested by predicting the construction costs of residential and reinforced concrete buildings. Correlation analysis, PCA, and LASSO were used for feature selection to identify the most relevant variables, with the combination of LSMBM-PCA giving the best performance. When compared to other machine learning models, the LSMBM model achieved the lowest error values, with an RMSE of 0.016, MAE of 0.010, and MAPE of 4.569%. The overall performance measurement reference index (RI) further confirmed the superiority of LSMBM. Furthermore, LSMBM performed better than the Earned Value Management (EVM) method. LSMBM model has proven to enhanced the precision in predicting cost estimates, facilitating project managers to anticipate potential cost overruns and optimize resource allocation, provide information for strategic and operational decision-making processes in construction projects.*

KEYWORDS: *Cost estimation, Machine learning, Moment hyperplane, Feature selection, Earned value method.*

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1. INTRODUCTION

In the construction industry, estimating construction costs accurately is fundamental to project success. Cost estimation significantly impacts projects across their life cycle from initial planning and budgeting to resource allocation and project execution (Orgut et al., 2020). However, traditional cost estimation methods require significant human input and time to execute, which increases the risk of mistakes and errors. Thus, the quality of estimates significantly depends on the expertise and experience of the individual performing the analytical calculations (Wahab and Wang, 2022). Earned Value Management (EVM) is a powerful tool for predicting construction costs. However, it is affected by several important limitations, including being unable to account for resource constraints and external factors (e.g., labor productivity, market fluctuations, and weather conditions) that affect construction costs (Bagherpour et al., 2020). These externalities can introduce uncertainty levels that the EVM cannot address, necessitating the use of alternative approaches that consider these important variables to provide a more comprehensive perspective on project performance (Aramali et al., 2022). Therefore, there is an urgent need for advanced methods of construction cost estimation such as machine learning that are more sophisticated, accurate, data-driven, and adaptable to reduce cost-related risks and increase project success rates (Chandanshive and Kambekar, 2019). The ability of machine learning algorithms to quickly analyze historical project data and identify patterns, trends, and correlations facilitates the generation of more-accurate cost estimations that, when used in decision-making, reduce the risks of budget overruns and project delays (Elfaki et al., 2014). Machine learning leverages historical and real-time data, and can comprehend nonlinear relationships and variability that may be overlooked by the EVM approach. The combined approach of EVM and machine learning algorithms offers significant potential for improving the accuracy and reliability of estimating the cost of construction projects (Cheng and Hoang, 2014).

Construction cost estimation, a key element in managerial decision-making, has been investigated in various studies, several of which have focused on the potential of using machine learning algorithms. Chandanshive & Kambekar, and Bala et al. demonstrated the effectiveness of Backpropagation Neural Network (BPNN) in estimating construction costs in India and Nigeria (Chandanshive and Kambekar, 2019)(Bala et al., 2014). Arafa & Alqedra emphasized the importance of using larger datasets to improve the accuracy of BPNN (Arafa and Alqedra, 2010), and other studies such as Kim et al. and Guaydin & Dogan found BPNN to be superior to case base reasoning (CBR), linear regression (LR), and other algorithms (Kim et al., 2004)(Günaydin and Doğan, 2004). However, despite the strong potential of BPNN, its sensitivity to quantity and quality is a weakness that requires the careful selection of variables. Artificial Neural Networks (ANN), as utilized by Bala et al. in construction cost prediction, have demonstrated the ability to learn and adapt from historical data (Bala et al., 2014). Son et al. and Peško et al. revealed the superiority of Support Vector Machines (SVM) over ANN, highlighting the advantages of SVM in handling complex data (Son et al., 2012) (Peško et al., 2017). Furthermore, Wang employed Fuzzy Logic to calculate the cost of construction projects through the calculation of similarity degree (Wang, 2017). Rafiei & Adeli explored the use of Deep Boltzmann Machines, offering a new approach for understanding and predicting cost variables (Rafiei and Adeli, 2018). Additionally, Juszczyk integrated ANN with SVM (ANN-SVM), demonstrating its effectiveness in predicting construction costs by leveraging the strengths of both models to handle nonlinear data (Juszczyk, 2020). Similarly, Jiang applied ANN with Radial Basis Function (ANN-RBF) networks, presenting another approach for approximating construction costs (Jiang, 2020). Although several related models have been developed, there remains significant room for developing even more advanced and accurate data-driven approaches that leverage machine learning techniques in this area. Least Square Support Vector Machine (LSSVM) has the advantage of being able to solve cost estimation problems both for data with original features and for data transformed into a high-dimensional space with kernel functions (Suykens and Vandewalle 1999). However, a significant drawback of LSSVM is their treatment of all datapoints as equally relevant without weighting, creating problems when some datapoints are more reliable than others in a given dataset and potentially reducing prediction accuracy and generating inaccurate predictions (Preetha et al., 2016). Given the complexity of the construction cost estimation, exploring the potential of generating accurate construction cost estimates using advanced techniques is critical. Moreover, previous studies have generally applied machine learning models without incorporating a feature selection mechanism to determine the precise factors influencing construction costs. Integrating feature selection methods could significantly improve the accuracy of cost predictions by ensuring that only the most influential variables are considered in the analysis of the model.

The Least Square Moment Balanced Machine (LSMBM), an advanced AI-based inference engine, is introduced in this study as a method to significantly improve the accuracy of construction project cost estimation. LSMBM enhances the conventional LSSVM approach by adding the concept of moment as a data weighting mechanism to identify the optimal hyperplane. The weight assigned to each datapoint is determined using the backpropagation neural network (BPNN), allowing the model to focus on more-reliable data. LSMBM employs feature selection techniques to enhance model efficiency by ensuring only the most influential construction cost factors are considered. Moreover, to provide a comprehensive perspective, the factors that influence construction costs are combined with EVM metrics. The proposed LSMBM is applied to estimate construction costs using actual data from residential and reinforced concrete (RC) building projects to validate model performance. In light of the critical role of cost management in construction project success, this study contributes to the development of more accurate and reliable cost estimation methods, enhancing decision-making in the construction industry by developing an AI-based inference engine that leverages knowledge and experience in relevant fields.

2. LITERATURE REVIEW

2.1 Construction cost at completion and influencing factors

The use of historical data in the cost-estimation process has received increasing attention in the construction management literature. Historical data from previously completed projects capture patterns and trends and provide valuable lessons for future projects (Al-Hazim et al., 2017). A systematic literature review was conducted to identify, evaluate, and synthesize all relevant research on factors influencing construction project costs (Dekkers et al., 2022). This approach ensured a comprehensive data collection from various sources, including peer-reviewed journals and conference proceedings across several electronic databases such as Scopus, Web of Science, and Google Scholar. The search strategy employed specific keywords like 'construction cost influencing factors', 'construction cost prediction model', and 'machine learning in construction cost estimation'. The inclusion criteria were carefully defined to select studies that directly contribute to the understanding and advancement of cost estimation factors in construction projects. These criteria included publication in peer-reviewed journals, publication in English, a specific focus on construction cost estimation, and publications from 2001 to the present, emphasizing the selection of the most relevant research. Conversely, exclusion criteria were set to omit articles that did not focus on construction projects or lacked empirical validation. Data extraction involved summarizing key findings related to the identification of cost-influencing factors in construction projects. The 20 academic articles identified and reviewed produced an initial list of 24 factors of influence, as summarized in Table 1. After analyzing these factors for frequency of citation in the scientific literature, project duration was identified as the most-frequently cited factor, followed closely by building costs, construction price variations, contract changes, and productivity, with each cited in more than 10 of the reviewed studies. Factors including material costs, weather conditions, total floor area, superstructure floors, and basement floors were also highlighted as important factors, with citations in 8~10 of the reviewed studies. In this study, the 10 factors with over five citations were extracted and included in subsequent analysis.

2.2 Earned Value Management and Machine Learning in Construction Cost Estimation

EVM is an effective project management technique for predicting construction costs. By integrating project scope, time, and cost data, it provides a comprehensive overview of project performance (Batselier and Vanhoucke, 2015). EVM operates by first establishing the planned value (PV), budget at completion (BAC), and actual duration (AD). Earned value (EV) is calculated based on the actual project work completed to date and then compared to the actual cost (AC) of work completed to date. The resulting cost variance (CV) and schedule variance (SV) provide insight into actual project performance versus initial estimates. These metrics may be further analyzed to generate performance indices such as the cost performance index (CPI) and schedule performance index (SPI). Furthermore, estimate cost to complete (ECTC) calculates the projected cost to complete the remaining work. Using ECTC allows project managers to monitor project progress and make dynamic changes in resource allocation and scheduling to ensure a project remains within budget (Anbari, 2003). The most basic formula for calculating ECTC, shown in Eq. (1). To expand its analytical, some methods incorporated AC into the equation, resulting in Eq. (2). Subsequent improvements to this formula involved incorporating efficiency indicators such as CPI, as shown in Eq. (3), and SPI, as shown in Eq. (4). In addition, a more comprehensive ECTC considers both cost and schedule efficiency simultaneously using weights, as shown in Eq. (5). This evolution of ECTC enables the formula to better adapt to the specific needs of individual projects.

$$ECTC = BAC - EV \tag{1}$$

$$ECTC = BAC - AC \tag{2}$$

$$ECTC = \frac{(BAC - EV)}{CPI} \tag{3}$$

$$ECTC = \frac{(BAC - EV)}{(CPI \times SPI)} \tag{4}$$

$$ECTC = \frac{(BAC - EV)}{(w_1 \times CPI + w_2 \times SPI)} \tag{5}$$

Numerous studies have validated the effectiveness of EVM in the construction domain. For instance, Zahoor et al. demonstrated that EVM could accurately forecast cost at completion for building projects (Zahoor et al., 2022), while Sruthi & Aravindan confirmed its predictive capabilities in residential projects, noting its ability to effectively manage project costs (Sruthi and Aravindan, 2020). However, Ibrahim et al. identified limitations of EVM, particularly its inability to address the complexities inherent in construction projects (Ibrahim et al., 2019). To address these limitations, Aramali et al. suggested integrating machine learning to enhance cost prediction accuracy (Aramali et al., 2022). The integration of historical data with machine learning offers a path for developing more-accurate tools for estimating construction costs (Wang et al., 2012). This approach utilizes patterns and trends from completed projects along with sophisticated models such as Regression Analysis (RA), ANN, and SVM. Alshamrani and Swei et al. demonstrated the widespread use of RA in various construction sectors to enhance estimation accuracy (Alshamrani, 2017)(Swei et al., 2017). Additionally, ANN has proven effective in surpassing EVM methods for predicting costs in building and road construction projects (Dursun and Stoy, 2016)(Tijanić et al., 2020)(Balali et al., 2020), and has shown superior performance in specialized applications such as water-related projects and hydroelectric power plant projects (Marzouk and Elkadi, 2016) (Gunduz and Sahin, 2015). El-Kholy et al. and ElMousalami et al. highlighted ANN's superiority over RA in various cost estimation tasks (El-Kholy et al., 2022)(ElMousalami et al., 2018). Moreover, studies comparing ANN and SVM have consistently shown SVM's robust performance in predicting construction costs, underscoring its reliability and enhanced accuracy, which is crucial for improving decision-making in construction cost management (Wang et al., 2012)(Petruseva et al., 2017)(Peško et al., 2017). This highlights SVM reliability and superior accuracy, improving decision-making in construction cost management.

3. LEAST SQUARE MOMENT BALANCED MACHINE FOR PREDICTING CONSTRUCTION COST

3.1 Model Structure

The principle of moment balance, which refers to the balance of the forces in a system, is important for designing and analyzing structures, particularly in the context of achieving stability in structural components. A basic beam subjected to a certain load that requires symmetrical moments for stability is shown in Figure 1. These moments, calculated as the product of the acting force (F) and its distance from the axis of rotation (d) may be formulated using Eq. (6). Unbalanced moments can cause various types of structural damage. In severe cases, these unbalanced moments can cause the entire structure to collapse (Deng et al., 2016). Therefore, it is critical to equip structures with the resilience necessary to withstand unbalanced moments.

Table 1: Significant factors of influence on construction project cost, ranked by number of citations in the literature.

No.	Factor	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	Freq
1	Project duration	●		●		●		●	●	●	●	●	●	●		●		●	●	●		14
2	Building cost	●		●	●						●	●	●	●	●	●	●			●	●	12
3	Construction price variation	●		●	●	●					●	●	●	●	●	●				●	●	12
4	Change in contract	●		●	●	●					●	●	●	●	●			●		●	●	12
5	Productivity			●	●	●					●	●	●	●	●				●	●	●	11
6	Material price			●	●						●	●	●	●	●	●				●	●	10
7	Weather condition	●		●		●					●	●	●		●					●	●	9
8	Total floor area		●	●			●	●	●	●	●					●	●					9
9	Superstructure Floors		●	●			●	●	●	●	●					●						8
10	Basement Floor		●	●			●	●	●	●	●					●						8
11	Site condition			●	●	●		●					●									5
12	Designer pricing									●		●	●			●						4
13	Building structure			●						●	●						●					4
14	Type of foundation		●	●			●									●						4
15	Politics				●							●	●		●							4
16	Building function							●					●					●				3
17	Geological condition											●			●					●		3
18	Safety				●									●						●		3
19	Building height						●	●														2
20	Number of columns		●				●															2
21	Type of client			●																●		2
22	Laws				●							●										2
23	Economy				●							●										2
24	Culture					●						●										2

1] Cheng & Hoang (2014); [2] Chandanshive & Kambekar (2019); [3] Toh et.al (2012); [4] Zhao et.al (2019); [5] Oberlender & Trost (2021); [6] Yun (2022); [7] Bala et.al (2014); [8] Kim et.al (2004); [9] Ji et.al (2019); [10] Hazim et.al (2017); [11] Aljohani (2017); [12] Kavuma et.al (2019); [13] Igwe et.al (2020); [14] Baloi & Price (2003); [15] Hyung et.al (2020); [16] Chakraborty et.al (2020); [17] Wang et.al (2012); [18] Juszczyk & Leśniak (2019); [19] Cha & Shin (2011); [20] Shah (2016)

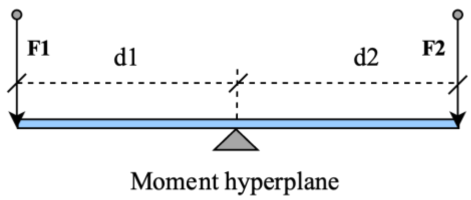


Figure 1: Moment balance on a simple beam.

$$m = \Sigma\ (Force * Distance) = 0 \tag{6}$$
$$m = F_1\, d_1 + F_2\, d_2 + \cdots + F_i\, d_i = 0$$

In machine learning, LSMBM uses the principle of balanced moments. The weight (F_k) is considered analogous to the force applied by each datapoint on the model, and its error (d_k), which represents the deviation of the predicted value from the true value, is analogous to the distance from the axis of rotation to the point where the force is applied. An example of a balanced moment hyperplane is shown in Figure 2. LSMBM incorporates the principles of LSSVM, which uses square errors to measure the degree to which model predictions deviate from the actual data. As the error value increases (d_k), the squared value (d_k^2) increases more rapidly. Squaring emphasizes larger errors over smaller ones, forcing the algorithm to increasingly focus on reducing these large errors to find the optimal solution.

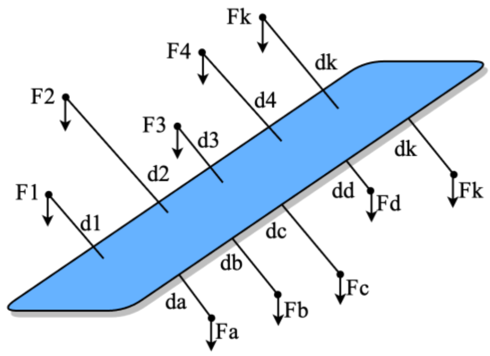


Figure 2: Balanced moment hyperplane.

The LSMBM uses a weights (F_k) mechanism to determine the influence of each datapoint to identify the optimal moment hyperplane. BPNN is used to determine the weights for each datapoint. The weights balance the influence of each datapoint on the overall model, which may be considered as a form of balancing as it adjusts the influence of each datapoint on the model based on the assigned weights. More-reliable datapoints are assigned higher weights to increase model accuracy, while less-reliable datapoints are assigned lower weights. The moment is the product of the weight and squared error that each datapoint contributes to the model ($F_k\ d_k^2$). The model architecture of LSMBM is illustrated in Figure 3.

Given a regression dataset associated with weights as shown in Eq (7), the objective function of the LSMBM model attempts to minimize the moment to achieve a balanced condition in the model, as shown in Eq. (8). This is an optimization problem that attempts to find the condition of balance among the moments of all datapoints.

$$D = \{(x_1, y_1, F_1), (x_2, y_2, F_2), \dots, (x_i, y_i, F_i)\} \in \mathbb{R}^n \tag{7}$$

$$\text{Minimize} \qquad J(w, d) = \frac{1}{2}||w||^2 + \gamma \frac{1}{2}\sum_{k=1}^{N} m$$
$$\text{Where: } m = F_k {d_k}^2 \tag{8}$$
$$\text{Subject to} \qquad y_k = w.\varphi(x_k) + b + d_k$$

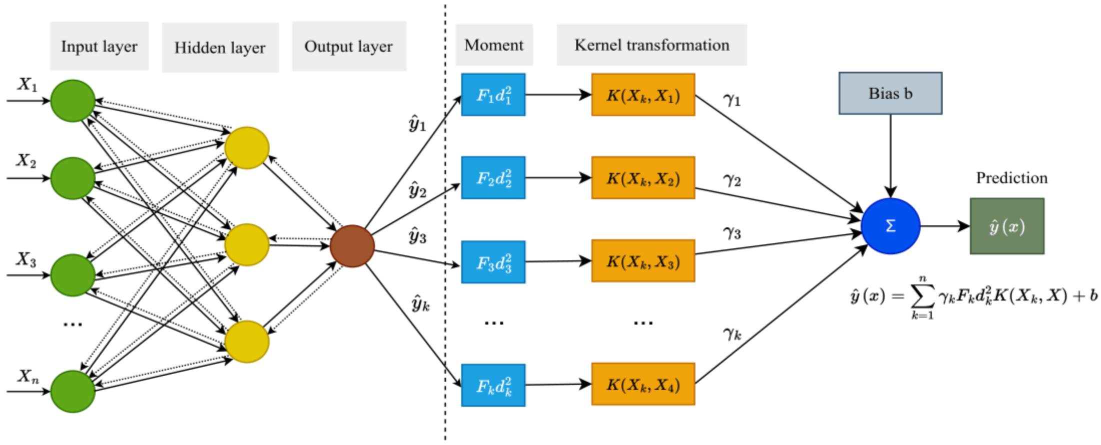


Figure 3: LSMBM model architecture.

Where x_k is the input; y_k is the output; (w) is the weight vector; (γ) is the regularization constant that controls the trade-off between model complexity and generalization; (m) is the moments given by each datapoint; (d_k) is the error; (n) is the number of datapoints; and (F_k) is the weight assigned to datapoint (x_k) obtained using the BPNN algorithm for the initial prediction. Smaller F_k values reduce the effect of parameter (d_k), which indicates a lower importance for the corresponding point (x_k). The weight of each case (F_i) may be calculated using Eq. (9), where Y_i and $\hat{Y}_i$ denote actual productivity and predicted productivity, respectively. To address the optimization challenges inherent in the LSMBM model, the mathematical formulation, including the derivation of a Lagrangian function, the selection of Lagrange multipliers (αk) and the application of a Radial Basis Function (RBF) kernel, is presented in Eq.(10)-(17) in Appendix A.

$$\begin{aligned} \text{Forecast error} &= \frac{\|\text{Actual-Prediction}\|}{\text{Actual}} = \frac{\|Y_i - \hat{Y}_i\|}{Y_i} \\ \text{Weight } (F_i) &= \frac{1}{\text{Forecast error}} = \left(\frac{\|Y_i - \hat{Y}_i\|}{Y_i}\right)^{-1} \end{aligned} \tag{9}$$

3.2 Model Adaptation

With regard to study methodology, in Stage 1, the construction costs dataset for RC buildings was established. In Stage 2, the input and output variables were identified using a review of the literature, and the former were refined for use in machine learning algorithms through normalization, using Eq. (18). In Stage 3, after data preprocessing, several feature selection methods were applied to identify significant features. In Stage 4, several different machine learning algorithms were applied to forecast construction costs. In the final stage, construction cost was estimated using the five performance metrics and a reference index. The general framework of this study is shown in Figure 4.

$$X_{norm} = \frac{(X_i - X_{min})}{(X_{max} - X_{min})} \tag{18}$$

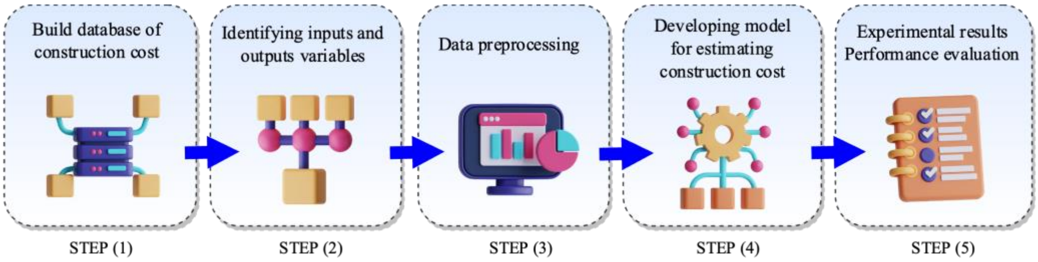


Figure 4: Framework used to develop the construction cost model.

The dataset comprising data from residential and reinforced concrete building projects was initially collected. The LSMBM adaptation then begins with data preprocessing, including normalization to ensure all input variables are on a uniform scale. Feature selection is a critical subsequent step, which employs Correlation Analysis (CA), Principal Component Analysis (PCA), and Least Absolute Shrinkage and Selection Operator (LASSO). A 10-fold cross-validation method was used to validate the generalizability of the proposed model. The dataset was divided into ten uniform, randomly distributed subsets, with nine used to train the machine learning model and the remaining one used to evaluate model performance. This iterative procedure was performed ten times, with each iteration using a different combination of the ten subsets (Bugalia et al., 2022). The resulting performance measures were averaged to provide an overall assessment of model performance. The training dataset incorporated both input and output variables. This allowed the model to capture the correlations and patterns between inputs and outputs, enabling it to effectively generalize and generate precise predictions from separate test datasets. These test subsets, which were separated from the training phase, were used to validate the performance of the trained predictive model. The main purpose of using these different test sets was to evaluate the ability of the model to generalize new data, with the performance of these independent datasets evaluated to assess model generalizability and predictive accuracy.

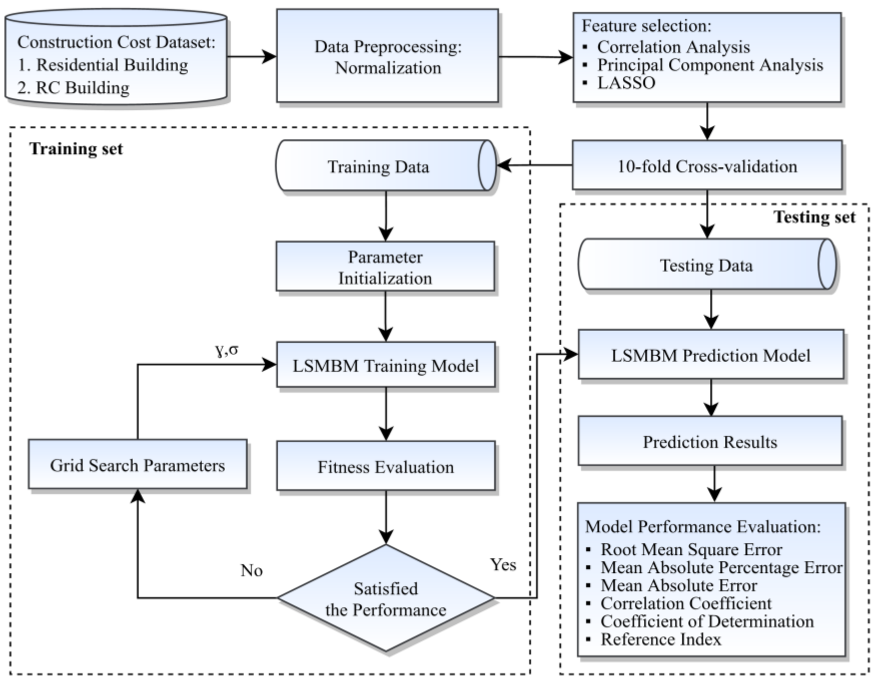


Figure 5: LSMBM model adaptation.

After learning the relationships between selected features and target variables from historical data, the LSMBM algorithm was used to make predictions based on these patterns. BPNN was trained on the training dataset, and initial predictions were used to calculate the weights. Lower prediction errors resulted in higher weights, which had a more significant influence on balancing the LSMBM model. The LSMBM hyperparameters, which include the regularization parameter (γ) and kernel parameter (σ), were then tuned using a grid search technique to determine the most effective combination of parameters. The models were run in a MATLAB library environment (Chang and Lin, 2011). In the fitness evaluation, the performance of the LSMBM model was evaluated using the error metric RMSE, with the model that achieved the lowest error selected as the best model. Subsequently, the model was used to predict the test data and validate its accuracy. The testing dataset is new to the model. The prediction result was the estimation value generated by the predictive model trained on the test dataset, which represented the predicted value of the output or target variable based on the input features provided. The five performance evaluation metrics were analyzed to assess model performance and a reference index was used to evaluate overall model performance. The sequence of operations used from initial data preprocessing to predictive performance evaluation to adapt the LSMBM is depicted in the flowchart in Figure 5.

3.3 Feature Selection

3.3.1 Correlation Analysis

Feature selection (FS) enhances model efficiency by ensuring only the most informative factors are retained. In this study, correlation analysis was applied to identify the factors with a significantly impact on construction costs (Puth et al., 2015). The strength and significance of correlations between variables were assessed using three methods: Pearson, Kendall's tau-b, and Spearman's rho. A threshold p-value of 0.05 ensured that factors consistently showing significant correlation across all methods were included in the final list. This approach ensured that the selected features demonstrate consistent relationships across different correlation measures.

3.3.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was used for feature selection to reduce the dimensionality of the data while maintaining variability. PCA provides valuable information regarding the most significant features (Shlens, 2014). A factor loading threshold of 0.3 was established, meaning that only variables with a factor loading of 0.3 or higher were considered relevant, while loadings below 0.3 were deemed insignificant (Jomthanachai et al., 2022). PCA results, supported by specific values and visualizations, offer a strong foundation for feature selection. Variance graphs, and 3D plots collectively provide a comprehensive understanding of the relationships between variables and the inherent data structure. The variables that contribute the most to each principal component may be determined by examining the direction and length of the vectors that represent the variables.

3.3.3 Penalized Linear Regression

Least Absolute Shrinkage and Selection Operator (LASSO) provide effective approaches to feature selection for high-dimensional data. These methods introduce a regularization penalty into the linear regression model, allowing for the identification of the most important features while controlling for overfitting (Muthukrishnan and Rohini, 2017). A key feature is its ability to shrink some coefficients to zero, which indicates the presence of redundancies among model features. This feature selection capability helps identify the subset of predictors most relevant to the target variable.

3.4 Performance Evaluation

Systematic evaluations are conducted to measure the accuracy and effectiveness of forecasting algorithms. Comparative analysis was performed using the following metrics: RMSE, mean absolute percentage error (MAPE), mean absolute error (MAE), correlation coefficient (R), and coefficient of determination (R2). These evaluation criteria measure the difference between the actual and predicted values of a target variable. An additional metric, the Reference Index (RI), was used as a composite measure representing the average result for a variable across all five metrics, giving equal significance to each (Cheng and Gosno, 2021). The values for each metric were first normalized and the calculated RI value was plotted on a scale from 0 (worst result) to 1 (best result). RI was calculated by averaging the normalized scores of the five evaluation metrics. RI value of 1 indicates optimal performance across all metrics. If the normalized score of any metric is less than 1, the RI value correspondingly decreases, representing an average based on the relative performance of all metrics. The mathematical formulations corresponding to this performance indicator are presented in Table 2.

Table 2: Performance evaluation.

Performance evaluation	Formula
RMSE	$\sqrt{\frac{1}{n}\sum_{i}^{n}(y_i - f_i)^2}$
MAPE	$\frac{100}{n}\sum_{i}^{n}\frac{\lvert y_i - f_i\rvert}{y_i}$
MAE	$\frac{1}{n}\sum_{i}^{n}\lvert y_i - f_i\rvert$
R	$\frac{n\sum_i^n y_i f_i - (\sum_i^n y_i)(\sum_i^n f_i)}{\sqrt{n(\sum_i^n y_i{}^2) - (\sum_i^n y_i)^2}\sqrt{\sqrt{n(\sum_i^n f_i{}^2)} - (\sum_i^n fi)^2}}$
R^2	$1 - \frac{\sum_i^n(y_i - f_i)^2}{\sum_i^n(y_i - \overline{y})^2}$
RI	$\frac{R_{norm} + R^2_{norm} + (1 - RMSE_{norm}) + (1 - MAE_{norm}) + (1 - MAPE_{norm})}{5}$

4. MODEL APPLICATION

4.1 Simulation 1: Residential Building Cost

To validate the capability and performance of the proposed LSMBM model, it was first applied to the residential buildings dataset collected by Rafieli et al. (Rafiei, 2018). The dataset can be found in Appendix B. This dataset comprises 372 instances of residential condominium buildings that range from three to nine stories, constructed between 1993 and 2008 in Iran. It includes seven input factors, with the construction cost as the output, as shown in Table 3. Feature selection was not performed in this case. The performance of the LSMBM model was benchmarked against various machine learning models, including LSSVM, BPNN, Random Forests (RF), Decision Trees (DT), K-Nearest Neighbors (KNN), linear regression (LR) and SVM. A grid search method was used to explore the combination of the regularization parameter (γ) and kernel parameter (σ). In this case, 10-fold cross-validation was applied to the training and testing datasets and the predetermined ranges for γ and σ [10-4, 10-3, 10-2, 10-1, 1, 101, 102, 103, 104], respectively, generated 81 parameter combinations. The selected ranges for γ and σ are consistent with values typically used in research applying SVM and related variants such as LSSVM, as supported by Balogun et al. (Balogun et al., 2021) and Dewi et al. (Dewi et al., 2023). The grid search explored 81 possible combinations and provided a systematic approach for determining the most optimal pair. The performance evaluation metrics, including RMSE, MAE, MAPE, R, R2, and RI, were employed to provide a comprehensive overview of the performance of each tested model. The summary of comparative results is presented in Table 4.

In the initial case, the proposed LSMBM outperforms the other models, delivering the lowest RMSE (26.940), MAE (19.533) and MAPE (12.07%). Furthermore, it achieves the highest R of 0.986, R^2 of 0.971, and RI of 1.000. It is closely followed by the LSSVM and BPNN models, which rank second and third, respectively. The RF and LR models show intermediate results, while the SVM, KNN, and DT models yield suboptimal outcomes. Overall, the LSMBM model excelled in terms of its prediction accuracy and reliability.

Table 3: Factors influencing construction costs in residential building.

Factors	Influence factor	Description
V1	Total floor area	area within the building
V2	Lot area	total land area of the construction site
V3	Total preliminary cost	the initial overall estimate for the project
V4	Preliminary cost	early cost estimation per m² before detailed planning
V5	Equivalent preliminary cost	adjusted estimate per m² for inflation or currency rates
V6	Duration of construction	time needed to complete the construction.
V7	Price of the unit	cost per m² for an individual residential unit
V8	Construction cost	the total cost required to complete the construction project

Table 4: Comparative performance metrics.

Model	RMSE	MAE	MAPE	R	R^2	RI	Rank
LSMBM	26.940	19.533	12.07	0.986	0.971	1.000	1
LSSVM	27.735	20.101	12.27	0.984	0.969	0.946	2
RF	39.965	25.019	14.17	0.974	0.949	0.468	4
BPNN	30.619	21.460	12.79	0.983	0.966	0.844	3
DT	47.376	29.804	15.56	0.961	0.924	0.021	8
KNN	47.950	28.410	15.41	0.961	0.924	0.050	7
SVM	44.801	30.483	15.62	0.970	0.941	0.174	6
LR	36.843	25.123	15.32	0.976	0.952	0.460	5

4.2 Simulation 2: Reinforced Concrete Building Cost

Data from 10 historical RC construction projects in Taiwan were employed as the second case study, collected by Cheng et al. (Cheng et al., 2019). These projects were selected based on the completeness of information available in terms of building information data, monthly construction reports, cash flow charts, and construction budgets. The number of superstructure floors ranged from seven to 14, while the number of basement floors varied from one to four. The contract values ranged from NTD 85 million to NTD 530 million. Total floor area varied from 3,094 square meters to 31,797 square meters. Project duration varied from 15 months to 25 months. Using the obtained information, each case was divided into 14-26 periods, resulting in 225 periods that formed the dataset for the model. The basic information for the 10 construction projects is shown in Table 5. After building the construction cost database, the factors influencing construction costs were identified and used as input data. The dataset included 18 input variables and one output variable. The dataset can be found in Appendix C. Before being input into the machine learning algorithm, the dataset was normalized to a range of 0 to 1, to ensure all variables were evaluated on the same scale.

Table 5: Overview of 10 construction projects.

ID	Basement Floors	Super-structure Floors	Total area	Contract price (NTD)	Duration (days)	Project start	Project Finish	Number of periods
A	9	2	12622	289,992,000	630	12/01/2003	08/22/2005	28
B	2	14	7707	153,500,000	695	11/24/2001	10/20/2003	21
C	3	14	10087	216,000,000	749	06/18/2002	07/06/2004	26
D	1	10	3479	85,714,286	486	06/02/2003	09/30/2004	17
E	2	7	3094	102,500,000	515	10/01/2005	02/28/2007	16
F	2	9	31797	530,000,000	635	07/04/2001	03/31/2003	19
G	3	11	4919	149,300,000	698	12/23/2003	11/10/2005	23
H	2	11	4774	145,337,589	730	02/21/2004	02/20/2006	26
I	4	11	6352	202,241,810	715	03/05/2004	02/18/2006	30
J	8	2	7289	190,844,707	457	06/15/2005	09/15/2006	19

4.2.1 Determination of Input- Output Variables

The study combined factors affecting construction costs with EVM metrics, which were used as input data, as shown in Table 6. The input data cover the four main categories of structural components, financial metrics, progress and duration, and performance and environment. First, structural components include the number of superstructure and basement floors, and the total floor area, which are fundamental for estimating costs due to their impact on materials, labor, and time requirements. Second, financial metrics cover indicators such as contract prices and payments, subcontractor billing indexes, and contract amount changes, alongside broader economic variables like price indexes and variations that affect the budget and potential cost deviations. Third, progress and duration measures, such as actual project duration and percentage of work completed, are crucial for predicting cost escalation impacts and monitoring project progress against the plan. Deviations in these metrics can significantly affect project costs and financial predictions. Fourth, performance and environment category includes efficiency metrics such as the schedule performance index, cost performance index, critical ratio, and productivity index, which are essential for evaluating progress and expenditure. External factors that potentially impact overall construction costs, such as weather conditions, were also considered. Inclement weather can cause project delays and increased labor costs, thereby increasing the overall cost of the construction project.

Table 6: Selected input variables.

Factors	Influence factor	Description
F1	Superstructure	Number of superstructure floors in building
F2	Basement	Number of basement floors in building
F3	Total floor area	Total area contained within the building
F4	Contract price	Total amount of the budget
F5	Actual duration	Cumulative work duration/contract duration
F6	Percent of actual work completed	ΣEV/BAC
F7	Percent of budget spent	ΣAC/BAC
F8	Percent of scheduled work completed	ΣPV/BAC
F9	Schedule Performance (SPI)	EV/PV
F10	Cost Performance (CPI)	EV/AC
F11	Critical Ratio	SPI x CPI
F12	Contract payment	Owner billed amount/EV
F13	Subcontractor billed index	Subcontractor billed amount/AC
F14	Construction price variation	Monthly construction price index /initial index
F15	Change in contract amount	Final contract amount/initial contract amount
F16	Weather impact	(Project duration – number of rainy day)/ project duration
F17	Productivity Index	Construction productivity index
F18	Project price index	Construction material price index

4.2.2 Correlation Analysis Results

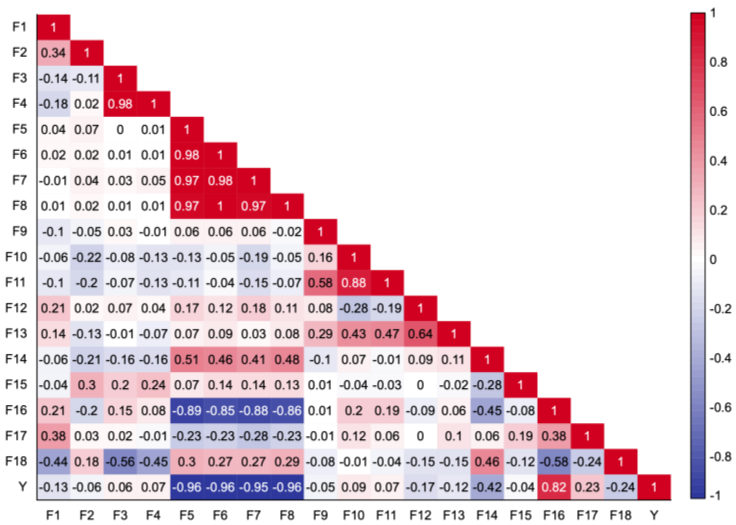


Figure 6: Pearson correlation.

Pearson's correlation measures the linear relationship between variables, and the correlation matrix is a visual representation that explains the relationships among different variables. The correlation matrix for the 18 input variables in this study is shown in Figure 6. To be considered significant, variables were required to earn correlation values below the threshold p-value of 0.05. From the correlation analysis, features F5-F8, F14, and F16-F18 were found to share strong linear correlations ($\rho < 0.05$) with the target variable. Kendall's tau analysis supported these findings, highlighting strong relationships for features F5-F8 and F14-F18. Spearman's rank correlation analysis reinforced Kendall's tau results. After evaluating the correlations for the 18 initial input variables, only eight (F5-F8, F14, F16-F18) met the significance threshold ($\rho < 0.05$) across all three correlation tests and were retained as input variables in the construction cost prediction model.

4.2.3 Results of the PCA Method

The variance graph shows the cumulative percentage of the variance explained by each principal component, and Figure 7(a) provides a visual representation of the proportion of total variance represented by each principal component. The principal (PC1), second (PC2), third (PC3), and fourth (PC4) components accounted, respectively, for 43.15%, 16.74%, 13.73%, and 9.06% of the total variance and together captured 82.67% of the total variance in the data, indicating these components capture most of the information presented in the original features. The 3D representation of PCA in Figure 7(b) provides a more comprehensive understanding of the data by facilitating the exploration of the relationships between variables in a three-dimensional space. Here, F5-F8 and F16 are shown to strongly influence PC1 and F3, F4, and F18 are shown to influence PC2. Furthermore, F1 and F2 are shown to contribute to PC3, while F2 and F14 are shown to contribute significantly to PC4. Based on the PCA results, 11 variables were identified as significant contributors, including F1-F8, F14, F16, and F18.

4.2.4 Results of the Penalized Linear Regression Method

The regularization penalty introduced by LASSO into linear regression models facilitates the identification of the most important features by providing an effective approach to feature selection for high-dimensional data. After applying LASSO regression, only 10 of the 18 initial input variables were retained, namely F3-F5, F7, F8, F13-F16, and F18. The results of the three feature analyses are summarized in Table 7.

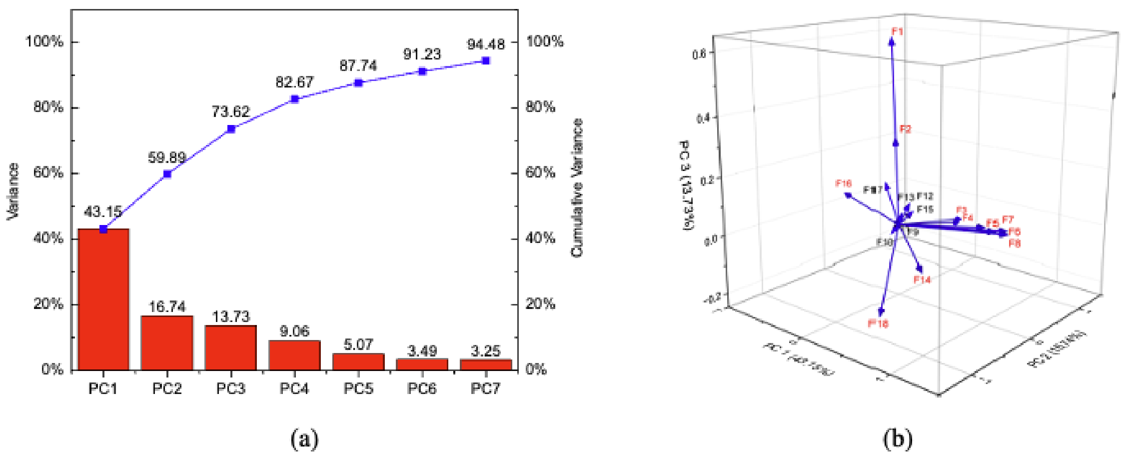


Figure 7: (a) the percentage of variance on PCA, (b) 3D PCA.

Table 7: Summary of the feature selection process.

ID	Correlation			PCA	LASSO
	Pearson	Kendall's tau-b	Spearman's rho		
F1				◉	
F2				◉	
F3				◉	◉
F4				◉	◉
F5	◉	◉	◉	◉	◉
F6	◉	◉	◉	◉	
F7	◉	◉	◉	◉	◉
F8	◉	◉	◉	◉	◉
F9					
F10					
F11					
F12	◉				
F13					◉
F14	◉	◉	◉	◉	◉
F15		◉	◉		◉
F16	◉	◉	◉	◉	◉
F17	◉	◉	◉		
F18	◉	◉	◉	◉	◉

4.2.1 Model Testing

In this study, the performance of LSMBM in predicting construction costs was evaluated using three feature selection approaches: correlation analysis, PCA, and LASSO. A grid search method was used to explore the combination of the regularization parameter (γ) and kernel parameter (σ). In this case, 10-fold cross-validation was applied to the training and testing datasets and the predetermined ranges for γ [0.01, 0.1, 1, 10, 100] and σ [0.01, 0.1, 1, 10, 100] generated 25 parameter combinations. These ranges align with commonly used values in studies that employ SVM and its variants like LSSVM (Balogun et al., 2021)(Dewi et al., 2023). By exploring 25 different combinations, the grid search provides a systematic approach for identifying the most optimal pair. The performance evaluation metrics were employed to provide a comprehensive overview of the performance of each tested model. A summary of these performance evaluations is provided in Table 8 and Table 9.

When correlation analysis was used as its feature selection mechanism, LSMBM consistently surpassed the benchmark models on all performance indicators in both training and testing stages. In the testing phase, LSMBM earned the lowest RMSE, MAE, and MAPE values (0.041, 0.028, and 10.081%, respectively), surpassing the 0.045, 0.031%, and 11.243% earned by the second-best model, LSSVM. The 0.991 and 0.982 earned by LSMBM for R and R2, respectively, indicate the proposed model is not only efficient at modeling training data but also highly generalizable to unseen data as well. Notably, the performances of RF and BPNN were inferior to LSMBM and LSSVM. A similar trend was also observed for the PCA, with LSMBM earning the lowest error values (RMSE = 0.016 and MAPE = 4.569%) and LSSVM earning the second-lowest (RMSE = 0.024 and MAPE = 7.984%). In addition, the R and R2 values of the LSMBM confirmed its reliability and stability under various conditions. Furthermore, when LASSO was applied to the feature selection, LSMBM achieved the lowest error values of all of the models.

Overall, the combination of LSMBM with PCA performed better than all of the other feature selection methods. The comprehensive evaluation conducted in this research demonstrated that the proposed LSMBM consistently outperforms the other machine learning models across all three feature selection techniques. This superiority was demonstrated through performance metrics in both training and testing phases. Moreover, LSMBM exhibited the highest RI among all of the feature selection methods, indicating its overall top-ranking performance. The parallel diagram shown in Figure 8 illustrates the performance of the combined LSMBM and PCA, with each horizontal line connecting average error measurements associated with a particular algorithm. For RMSE, MAPE, and MAE, lower values indicate better performance, while for R, R2, and RI, higher values indicate better performance.

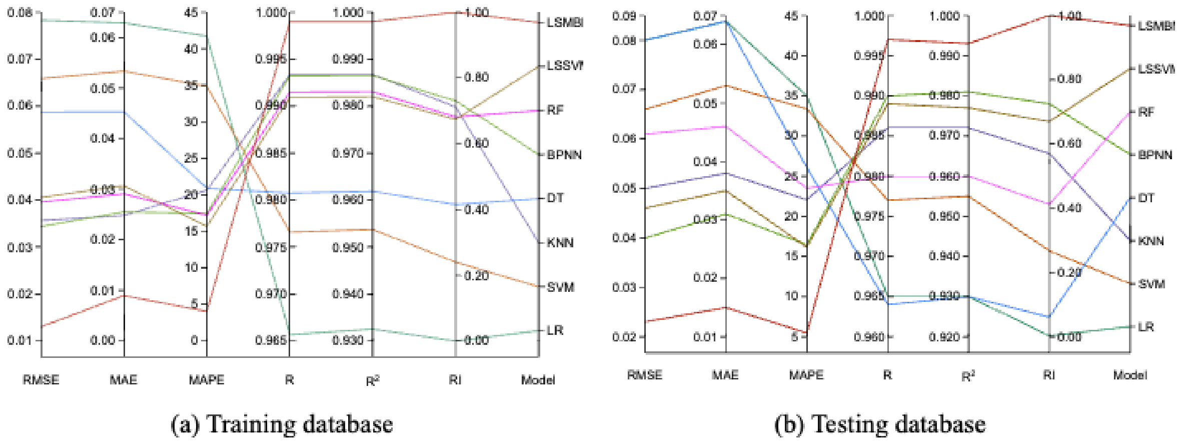


Figure 8: Performance evaluation of the combined LSMBM and PCA.

Next, the performance of LSMBM was compared to EVM using Eq. (1) - Eq. (5). The results obtained by LSMBM and several EVM methods are given in Table 10, with LSMBM exhibiting the best performance for all metrics. LSMBM achieved the lowest error values with an RMSE of 0.016, MAE of 0.010, and MAPE of 4.569, demonstrating high resilience and accuracy. Moreover, earning the highest R and R2 values indicates that the proposed model generalizes well to unseen data. Furthermore, the overall performance measurement using RI emphasizes the superiority of LSMBM to traditional EVM techniques in terms of predicting ECTC.

Table 9: Summary of LSMBM Performance Evaluations.

FS	RMSE	MAPE	MAE	R	R^2	Normalize					RI	Rank
						RMSE	MAPE	MAE	R	R^2		
CA	0.041	0.028	10.081	0.991	0.982	1.000	1.000	0.878	0.000	0.000	0.024	3
PCA	0.016	0.010	4.569	0.999	0.997	0.000	0.000	0.000	1.000	1.000	1.000	1
LASSO	0.034	0.025	10.849	0.993	0.987	0.720	0.833	1.000	0.250	0.333	0.206	2

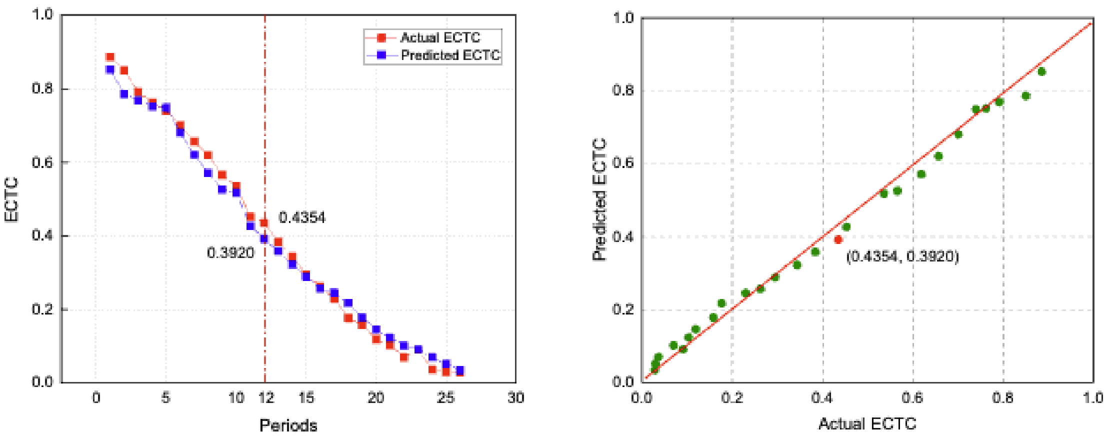
Table 10: LSMBM and EVM results comparison.

Method	RMSE	MAE	MAPE	R	R^2	RI	Rank
LSMBM	0.016	0.010	4.569	0.999	0.997	1.000	1
$ECTC_1$	0.100	0.076	60.306	0.956	0.913	0.646	2
$ECTC_2$	0.127	0.102	82.127	0.936	0.877	0.505	3
$ECTC_3$	0.211	0.132	63.868	0.846	0.729	0.300	5
$ECTC_4$	0.405	0.181	70.211	0.789	0.405	0.031	6
$ECTC_5$	0.198	0.124	63.403	0.859	0.198	0.343	4

Table 8: Summary of Model Performance Evaluations.

FS	Models	RMSE	MAE	MAPE	R	R^2	RI	Rank
Correlation analysis	LSMBM	0.041	0.028	10.081	0.991	0.982	1.000	1
	LSSVM	0.045	0.031	11.243	0.989	0.977	0.951	2
	RF	0.070	0.055	26.368	0.972	0.944	0.559	4
	BPNN	0.058	0.045	20.746	0.981	0.963	0.748	3
	DT	0.083	0.067	26.421	0.960	0.922	0.381	7
	KNN	0.072	0.058	27.224	0.972	0.944	0.542	5
	SVM	0.076	0.063	37.351	0.967	0.935	0.418	6
	LR	0.101	0.086	47.803	0.943	0.889	0.000	8
PCA	LSMBM	0.016	0.010	4.569	0.999	0.997	1.000	1
	LSSVM	0.024	0.015	7.894	0.997	0.994	0.918	2
	RF	0.061	0.046	23.117	0.980	0.960	0.407	5
	BPNN	0.040	0.031	16.444	0.990	0.981	0.688	3
	DT	0.080	0.064	26.057	0.964	0.930	0.086	7
	KNN	0.050	0.038	22.067	0.986	0.972	0.551	4
	SVM	0.066	0.053	33.368	0.977	0.955	0.283	6
	LR	0.081	0.064	42.020	0.965	0.930	0.003	8
LASSO	LSMBM	0.034	0.025	10.849	0.993	0.987	1.000	1
	LSSVM	0.038	0.027	12.011	0.992	0.985	0.949	2
	RF	0.058	0.044	21.534	0.981	0.963	0.536	4
	BPNN	0.066	0.051	21.308	0.976	0.952	0.382	5
	DT	0.080	0.064	26.064	0.966	0.933	0.076	7
	KNN	0.059	0.041	19.576	0.982	0.964	0.569	3
	SVM	0.069	0.056	32.124	0.975	0.951	0.243	6
	LR	0.079	0.065	32.969	0.965	0.932	0.005	8

4.2.2 Model Application



(a) (b)

Figure 9: (a) Actual and predicted ECTC; (b) Correlation with ECTC.

An RC project implemented by a construction company in Taiwan was used as the case study in this research, and the primary factors of influence on construction costs provided the framework for analyzing the case data. The project encompassed a total floor area of 4,774 square meters, including two basement floors and eleven superstructure floors. It was governed by a contract valued at 145,377,589 NTD, spanning a total duration of 730 days from February 21, 2004, to February 20, 2006. The project was divided into 26 periods throughout its execution. The dataset can be found in Appendix D. The top-performing LSMBM-PCA combination was used as the predictive model in this study. All of the data were normalized to a range of 0 to 1 to improve model efficiency and reduce the risk of error. The LSMBM model with PCA feature selection was used to predict the remaining costs to complete a project at different periods. Comparing actual and predicted values, the model attained a high level of accuracy with an RMSE of 0.029, MAE of 0.025, MAPE of 15.29%, and R value of 0.998. The comparison graph of the actual and predicted ECTC and their correlation is shown in Figure 9. The estimated cost at completion (ECAC) value was calculated using Eq. (19).

Where AC is actual cost percentage, ECTC is estimate cost to completion percentage and BAC is budget at completion, as stated in the project contract information. Cost estimation is conducted at the midpoint of the project (i.e., the 12th period). When expenditures are deemed appropriate and acceptable, the project proceeds with its predetermined budget. However, when potential cost overruns are indicated, immediate action is taken to mitigate or avoid these overruns. Based on the results of the analysis model, the ECAC for the 12th period was determined as follows:

$$ECAC = (AC + ECTC) \times BAC \tag{19}$$

$$ECAC_{Actual} = (0.4815 + 0.4354) \text{ x } 145.377.589 = 133.296.711 \text{ (NTD)}$$

$$ECAC_{Predicted} = (0.4815 + 0.3920) \text{ x } 145.377.589 = 126.987.323 \text{ (NTD)}$$

The variation in contract price is determined by calculating the difference between the actual and predicted ECAC, as follows:

Variation from actual ECAC : 145,377,589 - 133,296,711 = 12,080,878 (NTD)

Variation from predicted ECAC : 145,377,589 - 126,987,323 = 18,390,266 (NTD)

The positive cost variance indicates that this project was completed under budget, earning a cost savings of 8.31% (12,108,878 NTD). The prediction results indicate that the project would earn a cost saving of 12.65% (18,390,266 NTD). To ensure that the project remains under budget, regular progress and budget consumption evaluations should be conducted to detect potential deviations as early as possible. Furthermore, periodic cost monitoring must be implemented to ensure that the project remains on track. This step is crucial to identifying and addressing potential cost overruns. The project team must ensure that each phase proceeds according to the budget plan to avoid deviations that may reduce the cost savings achieved.

4.3 Comparison With Previous Works

The performance of the proposed LSMBM-PCA model in this study was evaluated and compared with various methods proposed in previous research. Table 11 presents a comparison of the accuracy results for predicting construction cost estimates of building projects using various approaches. The methods used in the previous studies include ANN-SVM, ANN-RBF, Deep Boltzmann Machine, Fuzzy Logic, and ANN. Each method was tested by using different datasets and features. The accuracy indicates how closely the predictions of the model match the actual values, with higher percentages representing more accurate predictions. Prediction accuracy was defined as (100-MAPE)% (Bang et al., 2023). The range of accuracy achieved by the methods in previous studies varied between 89.9% - 95.08%. Meanwhile, the model proposed in this study, LSMBM-PCA, achieved the highest accuracy of 95.43%. The higher accuracy of the LSMBM-PCA model indicates the potential for improved predictive performance over existing methods. This enhancement represents a significant advancement in data-driven decision-making within construction cost management. This accuracy is crucial for effective project planning and budget allocation, rendering the LSMBM-PCA model an invaluable tool for project managers. It enables informed decisions regarding resource allocation, project feasibility, and contingency planning.

Table 11: Accuracy results with previous works over various datasets.

Authors	Method	Accuracy (%)
Juszczyk (2020)	ANN-SVM	95.08
Jiang (2020)	ANN-RBF	94.46
Rafiei & Adeli (2018)	Deep Boltzmann machine	89.9
Wang (2017)	Fuzzy Logic	95
Bala et al. (2014)	ANN	94.6
Present Study	LSMBM-PCA	95.43

4.4 Discussion and Limitations

4.4.1 Discussion

This study advances current construction cost prediction application capabilities by developing and validating the inference engine LSMBM as a significantly more accurate, AI-based tool for construction project cost estimation. The model has been successfully validated using two case studies. In the first case, the proposed LSMBM model surpasses other machine learning models in predicting construction costs of residential buildings. It consistently demonstrated superior performance across all evaluation metrics, making it the most reliable and accurate model among the tested models. In the second case, the integration into the LSMBM model of key factors that influence construction costs with EVM metrics offers significant potential to further improve the accuracy and reliability of construction project cost estimation for RC buildings. Three feature selection techniques, including Correlation Analysis, PCA, and LASSO, were used to identify the most relevant variables for accurate and reliable cost estimation.

In the correlation analysis test, the performance of LSMBM was superior to all of the other models on nearly all metrics. LSMBM exhibited the fewest error metrics, affirming its ability to predict construction costs at a high level of accuracy. Also, LSMBM earned the highest values for R and R^2 indicating robust predictive capabilities. An R^2 value closer to 1 indicates that the predictions are very close to the actual costs, providing project managers and stakeholders with a higher degree of confidence in making informed decisions and managing projects within budget constraints. This superiority was maintained when using PCA and LASSO for feature selection. The LSMBM consistently achieved top rankings in the RI metric across all feature selection methods. Particularly, the PCA and LSMBM combination yielded optimal results for cost prediction. The RI metric assigns equal weights to each performance indicator, evaluating and ranking overall performance to ensure that every metric contributes equally to the final index. A reinforced concrete project conducted by a Taiwanese construction company was used as the case study. The LSMBM-PCA model resulted in a low error value metric. Cost estimation was performed at the midpoint of the project, with the evaluation results indicating that the final cost would be 12.65% below the amount budgeted. The actual result for the project amounted to 8.31% below budget. To increase model accuracy, consistent progress and budget monitoring are necessary to detect and respond to deviations from the budget plan at each stage of the project.

This study demonstrated the LSMBM model to be an accurate tool for predicting construction project costs. The consistent ranking of the proposed model at the top of various evaluation metrics and feature selection method rankings underscores its practicality as an advanced AI-based inference engine. The integration of key variables and EVM metrics into the LSMBM framework offers a comprehensive approach to cost prediction that enhances the accuracy and reliability of estimates. Furthermore, using feature selection methods, particularly PCA, in combination with LSMBM was shown to generate the most accurate cost estimates. The adaptability and improved accuracy of the LSMBM model support project management by providing earlier insights into potential cost overruns and facilitating strategic resource allocation. The LSMBM-PCA model represents a significant advancement in data-driven decision-making within construction cost management. By improving the accuracy of cost estimation, the LSMBM model enables project managers to make more informed decisions, thereby reducing the risk of budget overruns and enhancing project delivery. This study contributes to the field of construction management by applying advanced machine learning techniques to improve the accuracy of cost estimation. These findings may serve as a basis for future studies and practical implementations to optimize the planning and control of completion costs in construction projects.

4.4.2 Limitations

LSMBM is a promising approach for enhancing the performance of machine learning tasks, particularly in the context of predicting construction costs. However, in terms of future use and development, this model has several limitations that must be considered. First, the focus of this study was limited to predicting construction costs on residential and reinforced concrete building projects. Future research can expand the scope to other types of construction projects, such as infrastructure projects. Second, LSMBM exhibits sensitivity to hyperparameter configurations, which may impact model performance under certain conditions. Therefore, more sophisticated methods of hyperparameter optimization should be explored in future research to improve the stability and effectiveness of the model. Additionally, enhancing model interpretability through methods such as SHAP analysis, ICE plots, and PDP plots could provide deeper insights into the factors that influence cost estimations. Finally, although the performance of LSMBM was compared with several existing machine learning algorithms, there remains room to expand the scope of comparison. Future research should incorporate more types of models to provide a more comprehensive overview of the strengths and weaknesses of each reviewed algorithm.

5. CONCLUSION

A transformative advancement in construction cost prediction using an advanced AI-based inference engine, the Least Square Moment Balanced Machine (LSMBM), was demonstrated in this study. LSMBM considers moments to determine the optimal moment hyperplane. Backpropagation Neural Network (BPNN) is used as the initial prediction to measure the weight of each case, and the principle of Least Square Support Vector Machines (LSSVM) is adopted to obtain the moment hyperplane. LSMBM integrated these innovative methods to improve the accuracy of construction cost predictions, which provide significant advantages in data-driven planning and budget estimation for construction projects. Using an AI-based inference engine that integrates extensive domain knowledge and experience gives construction managers the insights necessary to make more sophisticated decisions and to more rapidly adapt to changing on-site conditions to ensure projects remain on track and within the budget. In addition, the proposed model enables project managers to distribute resources more efficiently, reduce project costs, and take corrective actions to minimize construction costs.

The findings of this study verified the ability of LSMBM to predict construction costs for both residential and reinforced concrete building projects. Firstly, the proposed LSMBM outperforms the other models by achieving the lowest RMSE (26.940), MAE (19.533), and MAPE (12.07%) among all models for residential buildings. In addition, this model achieved the highest R (0.986) and R^2 (0.971) values. Secondly, the study employed three feature selection techniques, including correlational analysis, PCA, and LASSO. These methods are essential for recognizing the most important variables involved in achieving better and more reliable cost estimates for reinforced concrete buildings. A 10-fold cross-validation method was used to validate the generalizability of the proposed model. The combination of LSMBM with PCA earned in the lowest error values of RMSE 0.016, MAE 0.010, and MAPE 4.569%, indicating high robustness and accuracy. In addition, the high R and R^2 values indicate a strong correlation between the actual and predicted values, demonstrating that the model explains a high proportion of the variance in the actual data. Furthermore, the overall performance measurement using reference index (RI) further confirmed the superiority of LSMBM over the other machine learning models considered. Finally, the construction cost prediction performance of LSMBM was then compared with the earned value management (EVM) method, with results showing that LSMBM performed better for all metrics. To test LSMBM in practice, a case study of an RC project of a construction company in Taiwan was used. The result estimated that the project would be completed 12.56% below the original budget, generating a cost savings of 18,390,266 NTD. To ensure that projects remain within budget, progress and budget expenditure evaluations should be conducted periodically to detect potential deviations as early as possible.

In this study, LSMBM was shown to enhance the accuracy of construction project cost estimates. However, areas for further improvement and consideration remain. The success of the LSMBM in predicting construction costs may be replicated in applications targeted on other types of construction projects. Also, the performance of LSMBM may be affected by hyperparameter configurations, which may impact model performance under certain conditions. Subsequent studies may consider hyperparameter optimization. Lastly, future research should consider expanding the scope of performance comparison to additional machine learning algorithms to further investigate and validate the performance advantages of LSMBM.

DATA AVAILABILITY STATEMENTS

The code and dataset for this study are available at:

https://github.com/LSMBM/LeastSquareMBM

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APPENDIX A

To solve the optimization problems, the Lagrangian function of the objective function and the corresponding constraints are formulated as shown in Eq.(10). Where α_k is the Lagrange multiplier and φ_k is the higher-dimensional feature mapping for each sample x_k. Solving the minimization problem involves taking the partial derivative of L with respect to the primal variable (*w, b, dk*), as shown in Eqs. (11)-(13). After eliminating w and d, the following linear system is obtained, as shown in Eq. (14). The kernel function is applied, as shown in Eq.(15).

$$L(\alpha, w, b, d) = \left(\frac{1}{2}w.w + \gamma\frac{1}{2}\sum_{k=1}^{N} F_k {d_k}^2 - \sum_{k=1}^{N} \alpha_k (w.\varphi(x_k) + b + d_k - y_k)\right) \tag{10}$$

$$\frac{\partial L(\alpha, w, b, d)}{\partial w} = 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k\, \varphi(x_k) \tag{11}$$

$$\frac{\partial L(\alpha, w, b, d)}{\partial b} = 0 \rightarrow \sum_{k=1}^{N} \alpha_k = 0 \tag{12}$$

$$\frac{\partial L(\alpha, w, b, d)}{\partial d_k} = 0 \rightarrow \alpha_k = \gamma F_k d_k \tag{13}$$

$$\begin{pmatrix} 0 & -Y^T \\ Y & W \end{pmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Where:

$$y = [y_1; \ldots; y_N], 1 = [1; \ldots; 1]^T, \alpha = [\alpha_1; \ldots; \alpha_N] \tag{14}$$

$$w_{ij} = y_i y_j\, \varphi(x_i).\varphi(x_j) + (F_i\gamma)^{-1} I$$

$$K(x_k, x_l) = \varphi(x_k).\varphi(x_l) \tag{15}$$

The Lagrange multipliers α_k and the bias term b may be obtained by solving the set of linear equations, resulting in the LSMBM moment hyperplane for function estimation as shown in Eq. (16). This hyperplane is influenced by the weight F_k through the stationarity condition $\alpha_k = \gamma F_k d_k$, as shown in Eq. (13), which effectively modulates the impact of each datapoint on the model. A radial basis function (RBF) kernel utilizing the sigma (σ) parameter was used in this study both to capture the nonlinear relationships between input features and target outputs and to facilitate the modeling of complex patterns that may not exhibit linear separability in the original feature space. The Radial Basis Function (RBF) kernel formula is expressed in Eq. (17).

$$y(x) = \sum_{k=1}^{N} \alpha_k\, K(x_k, x_l) + b \tag{16}$$

$$K(x_i, x_j) = exp(-\sigma \|x_i - x_j\|^2) \tag{17}$$

APPENDIX B

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
1	3150	920	598.5	190	1010.84	16	1200	410
2	7600	1140	3040	400	963.81	23	2900	1000
3	4800	840	480	100	689.84	15	630	170
4	685	202	13.7	20	459.54	4	140	30
5	3000	800	1230	410	631.91	13	5000	700
6	2500	640	1050	420	647.32	12	4800	700
7	1810	492	1158.4	640	843.98	11	5700	900
8	1150	380	575	500	590.68	6	5300	600
9	2110	540	189.9	90	732.14	5	690	110
10	3030	930	515.1	170	1007.38	3	1500	190
11	750	200	90	120	846.15	6	1100	150
12	4080	790	530.4	130	759.17	7	1800	190
13	5030	1540	251.5	50	667.88	3	600	130
14	4040	890	1212	300	752.65	6	3800	450
15	4880	1070	1854.4	380	614	5	4100	520
16	1860	480	539.4	290	836.28	4	3300	380
17	1460	380	627.8	430	733.24	5	4700	590
18	15670	3440	7208.2	460	1010.5	5	3000	630
19	2620	670	1231.4	470	724.38	5	3900	650
20	5020	1110	1706.8	340	853.01	5	3300	450
21	1830	410	494.1	270	650.57	6	3700	300
22	3560	690	925.6	260	885.89	7	2500	360
23	1590	350	667.8	420	678.64	6	4900	620
24	3700	820	962	260	749.77	6	2600	380
25	1450	370	406	280	702.48	5	3800	370
26	1480	380	222	150	731.79	5	1700	190
27	6930	1780	485.1	70	718.57	5	590	90
28	2750	610	357.5	130	916.66	6	1300	160
29	3040	670	881.6	290	561.79	5	4900	440
30	3420	880	547.2	160	890.64	4	2000	180
31	2600	560	598	230	415.24	10	2100	400
32	3600	980	612	170	2648.04	7	250	145
33	900	300	351	390	755.51	6	2600	600
34	820	250	303.4	370	928.27	7	2400	580
35	680	260	20.4	30	639.5	3	170	40
36	1160	300	429.2	370	474.91	5	2400	480
37	1160	260	185.6	160	697.66	7	990	230
38	2820	620	310.2	110	536.64	6	1300	170

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
39	760	200	106.4	140	616.47	6	940	190
40	2250	690	765	340	853.01	3	2200	430
41	5540	850	1551.2	280	957.42	9	1200	440
42	1540	400	154	100	771.33	5	700	110
43	4230	820	169.2	40	780.14	7	200	160
44	1540	590	215.6	140	698.95	2	820	160
45	4330	1110	86.6	20	421.26	4	170	30
46	2710	600	867.2	320	637.72	6	2300	490
47	1350	350	270	200	576.74	5	1700	270
48	1260	330	189	150	875.96	5	790	210
49	1710	440	171	100	798.68	5	630	120
50	730	190	226.3	310	893.95	6	1800	450
51	450	120	58.5	130	913.31	7	690	160
52	610	160	183	300	597.86	6	2700	460
53	3160	700	537.2	170	694.97	6	1100	300
54	370	120	40.7	110	585.22	5	1200	140
55	690	160	89.7	130	770.35	8	990	190
56	2140	400	813.2	380	614	5	3200	530
57	7500	1260	2775	370	820.91	11	1800	700
58	2100	500	126	60	1158.47	11	300	180
59	4600	1000	2668	580	3436.93	11	1300	900
60	5200	800	208	40	958.39	13	120	130
61	1820	400	655.2	360	474.74	5	3400	450
62	1500	350	810	540	637.93	6	4300	650
63	3100	640	1798	580	647.79	7	4600	700
64	2260	440	158.2	70	569.44	7	620	80
65	1090	280	152.6	140	777.06	5	1500	180
66	2530	560	759	300	722.86	6	1800	330
67	4070	1040	895.4	220	634.42	4	1800	290
68	6000	1320	1800	300	752.65	5	2800	400
69	820	260	49.2	60	644.47	4	630	90
70	1150	300	80.5	70	718.57	5	620	90
71	4000	880	400	100	750.7	5	540	110
72	3240	630	680.4	210	715.52	7	2300	290
73	1380	360	110.4	80	735.87	5	630	100
74	2170	480	542.5	250	854.84	6	1500	340
75	1820	400	200.2	110	753.66	6	920	140
76	580	150	17.4	30	631.89	6	240	70
77	2120	470	572.4	270	650.57	6	2900	300

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
78	5110	980	1430.8	280	505.51	7	2800	410
79	3110	690	777.5	250	720.93	5	2600	340
80	2030	450	365.4	180	565.58	6	1800	260
81	4840	930	1452	300	541.61	7	3300	430
82	4090	900	1104.3	270	655.93	5	2200	370
83	3280	720	459.2	140	805.03	6	1200	150
84	1610	410	177.1	110	585.22	5	1700	140
85	1710	440	119.7	70	525.49	5	880	80
86	2100	380	819	390	601.08	4	2800	510
87	1800	500	954	530	626.12	7	1900	650
88	1900	550	437	230	1362.92	7	550	320
89	1895	550	379	200	1446.67	6	450	250
90	2100	450	546	260	816.95	5	600	330
91	2050	700	492	240	527.22	10	2100	450
92	1052	250	168.32	160	948.12	6	770	200
93	1650	432	264	160	851.23	5	550	200
94	3350	800	804	240	369.9	7	1300	370
95	1450	336	507.5	350	442.61	2	1800	400
96	1130	260	339	300	511.56	3	1400	390
97	1200	1100	300	250	451.35	7	980	370
98	1450	336	536.5	370	371.34	4	2300	390
99	1560	400	171.6	110	878.55	5	420	130
100	2740	610	767.2	280	542.42	6	1500	440
101	2120	470	508.8	240	817.74	6	1100	350
102	1650	510	181.5	110	651.83	3	820	120
103	1430	440	57.2	40	772.31	4	280	120
104	720	190	72	100	798.68	6	490	120
105	2070	400	269.1	130	723.64	7	730	170
106	1900	420	190	100	575.02	6	720	110
107	390	100	62.4	160	547.1	8	1000	220
108	1540	340	446.6	290	727.56	6	1500	430
109	2410	530	216.9	90	525.58	6	640	130
110	440	120	13.2	30	779.57	8	160	60
111	1430	320	42.9	30	477.9	6	170	30
112	1190	310	130.9	110	642.37	5	870	150
113	930	240	93	100	770.16	5	460	110
114	1660	430	282.2	170	728.63	5	1200	240
115	1800	560	36	20	459.54	4	110	30
116	1500	330	540	360	867.43	7	1300	440

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
117	2300	510	207	90	536.26	6	580	110
118	1600	360	272	170	728.63	7	1200	310
119	2140	470	235.4	110	663.38	6	660	140
120	2010	520	381.9	190	814.35	4	1200	240
121	2670	690	213.6	80	600.56	5	340	90
122	2290	710	91.6	40	637.2	3	190	70
123	2370	610	189.6	80	617.07	4	380	90
124	1700	380	493	290	494.51	7	1700	450
125	6740	1300	674	100	603.07	6	780	130
126	3180	700	1049.4	330	732.16	5	1600	430
127	2630	580	315.6	120	599.1	6	850	160
128	870	230	69.6	80	650.79	6	320	100
129	1810	400	488.7	270	538.07	6	2000	420
130	2190	490	503.7	230	786.46	6	1200	320
131	2500	640	300	120	599.1	4	810	140
132	3650	940	1168	320	802.83	5	1500	420
133	990	260	297	300	581.16	6	1700	470
134	2330	600	256.3	110	792.82	4	390	120
135	1190	310	107.1	90	632.29	5	500	110
136	2370	730	71.1	30	400.73	3	210	90
137	1040	270	41.6	40	534.3	5	210	60
138	5280	1160	1584	300	659.02	5	1500	420
139	760	200	174.8	230	786.46	11	810	400
140	920	210	119.6	130	649.02	8	1300	200
141	1020	270	142.8	140	829.6	6	840	180
142	1310	340	52.4	40	534.3	5	470	70
143	1040	270	93.6	90	718.81	5	810	110
144	200	60	6	30	718.79	11	230	140
145	2880	740	662.4	230	579.07	5	2300	300
146	1820	400	546	300	541.61	7	2600	430
147	3050	670	1006.5	330	508.61	5	4300	460
148	850	220	68	80	548.12	5	870	100
149	1070	210	42.8	40	772.31	9	430	110
150	540	140	70.2	130	759.17	7	1400	180
151	1800	400	378	210	659.84	6	2000	300
152	3260	720	489	150	642.91	5	1500	220
153	1450	320	377	260	443.35	7	3100	410
154	840	220	100.8	120	690.02	6	770	130
155	1330	300	172.9	130	649.02	7	1100	190

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
156	360	100	86.4	240	409.25	8	3300	390
157	1910	420	152.8	80	425.62	6	1000	110
158	350	143	122.5	350	442.61	3	1800	420
159	900	150	63	70	751.88	6	210	100
160	2190	420	459.9	210	652.57	7	1000	300
161	770	170	231	300	728.81	7	1400	440
162	1060	240	190.8	180	784.87	7	1100	250
163	3270	510	327	100	579.84	9	230	90
164	920	290	46	50	513.26	4	190	60
165	360	100	86.4	240	409.25	8	1600	400
166	680	180	40.8	60	644.47	6	300	90
167	940	250	94	100	723.33	6	550	120
168	7010	1200	1472.1	210	718.07	7	1200	300
169	1310	290	104.8	80	578.67	7	480	100
170	2110	470	189.9	90	620.86	5	490	110
171	1380	310	193.2	140	744.83	7	700	200
172	1540	400	154	100	555.04	5	870	140
173	1450	320	203	140	600.05	7	840	250
174	1980	440	495	250	549.19	6	1700	360
175	2390	610	71.7	30	585.11	4	170	50
176	1990	440	258.7	130	721.55	6	840	180
177	360	80	21.6	60	644.47	11	330	100
178	2240	430	134.4	60	434	8	390	90
179	1580	363	331.8	210	526.86	8	1200	350
180	1580	363	284.4	180	615.49	8	770	250
181	270	90	24.3	90	693.15	7	480	100
182	620	160	62	100	436.04	6	1100	150
183	1510	390	241.6	160	654.09	5	1100	210
184	470	120	14.1	30	579.23	7	330	90
185	1020	320	102	100	575.02	4	550	110
186	450	120	103.5	230	505.25	7	1700	390
187	530	140	148.4	280	542.42	7	1800	470
188	1050	270	115.5	110	612.31	6	840	140
189	640	250	96	150	654.06	2	1100	170
190	400	110	40	100	499.25	7	880	160
191	1300	290	247	190	735.11	7	1100	300
192	670	180	154.1	230	577.03	6	1700	350
193	510	160	15.3	30	654.64	5	150	50
194	780	200	241.8	310	753.11	6	1400	400

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
195	1060	280	349.8	330	795.15	5	1600	360
196	1580	410	47.4	30	585.11	5	210	70
197	1540	340	154	100	592.57	7	710	140
198	770	200	146.3	190	590.42	6	1300	240
199	550	140	44	80	578.67	7	530	100
200	970	250	97	100	583.97	6	360	140
201	500	130	145	290	523.56	7	920	420
202	1680	370	285.6	170	490.23	6	800	260
203	520	120	62.4	120	667.98	9	360	170
204	300	80	33	110	536.64	9	670	180
205	280	90	44.8	160	388.7	6	710	210
206	660	170	112.2	170	490.23	6	680	260
207	450	120	54	120	490.57	8	500	210
208	950	250	114	120	514.33	5	500	170
209	430	100	8.6	20	436.43	10	90	90
210	490	160	14.7	30	467.3	5	100	50
211	870	230	174	200	481.91	6	1300	220
212	220	70	30.8	140	478.71	7	770	210
213	600	160	12	20	392.14	6	110	60
214	2650	590	238.5	90	449.32	5	810	110
215	1370	300	109.6	80	476.68	7	640	100
216	700	180	42	60	488.09	6	250	80
217	1810	470	488.7	270	523.05	5	860	410
218	960	250	67.2	70	417.09	5	350	80
219	990	310	99	100	499.25	4	550	120
220	980	250	107.8	110	471.47	5	780	160
221	380	100	60.8	160	547.1	8	650	230
222	540	140	75.6	140	478.71	6	900	200
223	280	80	22.4	80	444.03	9	650	140
224	1000	260	20	20	436.43	5	80	30
225	2390	530	239	100	499.25	6	400	140
226	810	210	194.4	240	532.48	6	900	330
227	230	60	18.4	80	460.02	10	350	110
228	982.5	202.5	353.7	360	554.84	5	1900	500
229	740	190	37	50	361.67	6	340	70
230	700	220	63	90	521.86	4	220	70
231	960	220	67.2	70	405.89	7	140	60
232	620	160	31	50	342.57	6	320	70
233	730	230	14.6	20	397.43	5	150	30

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
234	1780	390	231.4	130	442.94	7	510	190
235	520	140	78	150	466.12	7	1200	220
236	930	240	46.5	50	513.26	6	220	80
237	670	180	46.9	70	539.11	6	290	80
238	550	140	77	140	439.9	7	1000	210
239	430	110	81.7	190	476.68	8	820	310
240	1230	270	98.4	80	474.06	6	680	100
241	840	215	218.4	260	1495.05	10	440	350
242	730	190	65.7	90	542.77	6	490	110
243	470	120	32.9	70	493.59	7	380	90
244	800	210	56	70	372.41	6	440	100
245	760	240	15.2	20	459.54	4	80	30
246	850	220	59.5	70	422.15	5	520	80
247	310	80	31	100	487.86	9	770	170
248	670	180	174.2	260	469.4	7	1100	380
249	1070	280	74.9	70	539.11	6	260	80
250	920	290	36.8	40	325.39	4	370	50
251	940	250	56.4	60	462.8	5	190	70
252	2490	550	199.2	80	467.18	6	700	120
253	1110	250	88.8	80	390.29	7	900	120
254	580	150	75.4	130	442.94	7	1100	190
255	330	90	23.1	70	414.8	9	320	100
256	720	190	165.6	230	354.48	6	1200	350
257	1080	240	205.2	190	343.02	6	1000	270
258	370	120	3.7	10	196.07	5	180	20
259	370	100	74	200	481.91	8	650	280
260	580	150	75.4	130	531.45	6	870	230
261	520	140	109.2	210	323.66	6	1000	320
262	350	110	35	100	499.25	6	550	130
263	620	160	136.4	220	375.15	6	1100	330
264	1120	290	358.4	320	421.99	6	1600	430
265	360	100	28.8	80	463.87	8	210	70
266	460	120	96.6	210	461.32	7	1300	360
267	400	110	40	100	428.61	8	740	160
268	430	110	73.1	170	409.62	7	650	210
269	1230	320	86.1	70	479.6	5	240	90
270	950	250	171	180	358.72	5	580	240
271	750	200	45	60	423.07	6	360	80
272	200	100	46	230	445.56	3	820	300

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
273	6700	2500	603	90	279.67	9	580	150
274	810	210	48.6	60	432.44	6	260	80
275	450	120	4.5	10	193.08	7	180	50
276	780	200	117	150	432.56	6	1000	230
277	940	250	244.4	260	400.72	5	1400	370
278	370	120	81.4	220	339.07	5	1600	310
279	8800	2960	264	30	231.4	8	700	50
280	1750	300	52.5	30	400.73	10	130	60
281	1520	470	60.8	40	289.33	4	250	60
282	2170	480	195.3	90	439.07	6	340	130
283	1020	230	71.4	70	408.78	7	290	100
284	1410	310	239.7	170	338.79	6	960	270
285	1360	350	149.6	110	374.8	5	400	150
286	970	250	9.7	10	196.07	5	100	20
287	420	110	79.8	190	307	8	750	310
288	530	140	31.8	60	350.38	7	450	90
289	1920	490	115.2	60	411.09	4	300	70
290	690	180	89.7	130	444.52	6	540	190
291	500	110	25	50	459.92	9	160	70
292	520	140	36.4	70	305.23	6	330	110
293	1510	330	166.1	110	341.82	6	640	140
294	540	140	113.4	210	406.81	7	610	350
295	470	130	126.9	270	416.13	7	750	430
296	630	170	163.8	260	342.87	6	1100	350
297	370	80	51.8	140	337.33	14	470	270
298	1670	370	83.5	50	291.99	7	410	80
299	630	160	107.1	170	412.99	6	810	220
300	680	160	142.8	210	379.13	8	900	330
301	1380	360	289.8	210	339.32	5	690	300
302	550	150	22	40	308.06	7	200	50
303	1510	330	392.6	260	400.72	6	960	390
304	990	260	158.4	160	402.83	5	830	210
305	1700	290	323	190	417.38	9	820	340
306	1120	250	246.4	220	339.07	7	1200	350
307	600	160	72	120	291.53	6	630	160
308	1160	260	92.8	80	352.27	7	400	120
309	450	120	81	180	324.97	7	920	270
310	610	160	73.2	120	302.12	7	440	160
311	800	250	8	10	229.77	4	40	20

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
312	480	130	62.4	130	403.97	7	420	190
313	1210	270	193.6	160	318.86	7	680	260
314	1910	420	305.6	160	388.7	6	810	210
315	1230	270	123	100	341.94	6	630	140
316	1540	340	338.8	220	339.07	6	660	330
317	1380	360	82.8	60	245.28	5	430	90
318	950	250	133	140	337.33	6	610	160
319	1980	510	336.6	170	329.32	5	790	260
320	280	90	11.2	40	325.39	6	180	50
321	1000	260	160	160	309.95	5	860	250
322	1530	390	15.3	10	193.08	5	120	40
323	640	170	102.4	160	351.48	6	700	230
324	400	130	36	90	307.74	5	330	110
325	410	110	20.5	50	301.54	8	400	70
326	520	140	57.2	110	341.82	7	420	160
327	2020	450	282.8	140	310.61	6	500	200
328	830	260	24.9	30	216.22	4	190	40
329	810	210	251.1	310	408.8	6	810	420
330	2620	580	786	300	395.62	6	1000	400
331	510	130	20.4	40	300.28	7	150	50
332	1150	260	161	140	307.54	7	990	240
333	1160	260	313.2	270	436.27	7	1200	420
334	940	240	141	150	377.65	6	430	220
335	540	140	37.8	70	372.41	7	420	100
336	1650	430	297	180	433.72	5	490	200
337	1820	470	382.2	210	379.13	5	720	300
338	2690	590	591.8	220	339.07	6	1000	330
339	1600	410	368	230	295.21	5	1500	300
340	14500	4870	3480	240	303.5	11	750	350
341	5500	1760	1100	200	341.04	6	670	300
342	14500	5000	580	40	237.03	7	220	60
343	1560	520	624	400	422.6	6	2300	450
344	810	250	32.4	40	274.06	5	570	50
345	840	190	67.2	80	273.55	8	650	120
346	1070	280	160.5	150	290.58	6	1500	240
347	1060	330	21.2	20	205.31	4	210	30
348	1390	360	41.7	30	206.95	4	350	40
349	560	220	22.4	40	319.47	3	350	50
350	580	150	104.4	180	348.7	7	1400	300

No	Total floor area	Lot area	Total preliminary cost	Preliminary cost	Equivalent preliminary cost	Duration of construction	Price of the unit	Construction cost
351	2350	610	423	180	324.97	4	860	220
352	910	240	163.8	180	277.42	6	960	270
353	830	260	41.5	50	287.51	4	600	60
354	1590	410	333.9	210	323.66	5	1100	290
355	1170	300	163.8	140	337.33	6	510	160
356	3080	680	215.6	70	238.51	5	850	100
357	1120	290	190.4	170	306.91	5	1600	240
358	810	250	32.4	40	275.94	4	390	50
359	870	230	208.8	240	308.05	5	1300	320
360	2310	600	531.3	230	303.3	4	1400	280
361	1370	360	191.8	140	271.21	5	1200	220
362	3400	750	714	210	323.66	6	2200	310
363	2100	600	210	100	288.37	10	640	190
364	1840	420	220.8	120	263.61	5	1500	170
365	1520	350	212.8	140	310.61	13	1200	300
366	2500	510	325	130	251.84	6	1100	200
367	900	250	45	50	278.32	7	350	70
368	1350	350	108	80	251.37	9	830	150
369	600	150	36	60	299.55	6	570	80
370	1900	430	285	150	364.41	7	640	220
371	510	160	30.6	60	245.28	9	790	110
372	890	230	35.6	40	237.03	6	350	50

APPENDIX C

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
1	9	2	12622	289992000	3.82	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	107	65	1.09
2	9	2	12622	289992000	7.89	0.04	0.02	0.05	0.69	2.01	1.39	1.00	1.00	1.03	1.00	0.99	109	68	1.07
3	9	2	12622	289992000	11.71	0.08	0.03	0.09	0.89	2.24	1.99	0.75	1.67	1.09	1.00	0.98	109	73	1.05
4	9	2	12622	289992000	15.79	0.10	0.05	0.10	0.99	2.05	2.03	0.65	1.33	1.12	1.00	0.97	109	76	1.04
5	9	2	12622	289992000	19.87	0.11	0.09	0.11	0.99	1.27	1.26	0.57	0.73	1.11	1.00	0.96	109	75	1.00
6	9	2	12622	289992000	23.82	0.12	0.12	0.12	1.00	1.02	1.02	1.05	1.07	1.10	1.00	0.95	109	74	0.97
7	9	2	12622	289992000	27.89	0.14	0.14	0.14	0.99	1.00	0.99	1.06	1.06	1.10	1.00	0.95	109	73	0.95
8	9	2	12622	289992000	31.84	0.15	0.15	0.15	1.00	1.04	1.04	1.09	1.14	1.12	1.00	0.94	109	75	0.94
9	9	2	12622	289992000	35.92	0.17	0.18	0.16	1.02	0.92	0.94	0.99	0.91	1.13	1.00	0.92	109	76	0.90
10	9	2	12622	289992000	40.00	0.17	0.23	0.16	1.02	0.73	0.74	0.93	0.68	1.13	1.00	0.91	109	76	0.86
11	9	2	12622	289992000	43.95	0.23	0.27	0.25	0.93	0.86	0.80	0.75	0.64	1.14	1.00	0.90	109	77	0.82
12	9	2	12622	289992000	48.03	0.30	0.32	0.30	1.02	0.95	0.97	0.75	0.71	1.13	1.00	0.90	109	76	0.77
13	9	2	12622	289992000	51.97	0.33	0.37	0.35	0.94	0.88	0.83	0.78	0.69	1.12	1.00	0.90	109	75	0.71
14	9	2	12622	289992000	56.05	0.39	0.40	0.41	0.95	0.97	0.92	0.77	0.74	1.12	1.00	0.89	102	75	0.68
15	9	2	12622	289992000	59.87	0.43	0.42	0.45	0.95	1.02	0.97	0.79	0.81	1.12	1.00	0.88	102	75	0.67
16	9	2	12622	289992000	67.89	0.57	0.47	0.61	0.94	1.20	1.13	0.70	0.84	1.13	1.00	0.87	102	75	0.61
17	9	2	12622	289992000	71.84	0.67	0.53	0.70	0.95	1.26	1.20	0.68	0.86	1.12	1.00	0.86	102	76	0.56
18	9	2	12622	289992000	75.92	0.76	0.63	0.79	0.96	1.21	1.16	0.72	0.87	1.11	1.00	0.84	102	75	0.46
19	9	2	12622	289992000	79.87	0.86	0.71	0.88	0.97	1.20	1.16	0.73	0.88	1.11	1.00	0.83	102	74	0.37
20	9	2	12622	289992000	83.95	0.97	0.84	0.98	0.99	1.16	1.15	0.83	0.97	1.11	1.00	0.82	102	73	0.25
21	9	2	12622	289992000	88.03	0.98	0.92	0.99	0.99	1.07	1.06	0.82	0.88	1.12	1.00	0.81	102	73	0.17
22	9	2	12622	289992000	91.97	0.99	0.94	0.99	0.99	1.05	1.04	0.91	0.95	1.12	1.00	0.80	102	74	0.15
23	9	2	12622	289992000	96.05	1.00	0.97	1.01	0.99	1.03	1.02	0.89	0.92	1.12	1.01	0.80	102	74	0.12
24	9	2	12622	289992000	100.00	1.00	0.99	1.01	0.99	1.01	1.00	0.89	0.91	1.12	1.01	0.79	102	74	0.10

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
25	9	2	12622	289992000	104.08	1.01	1.00	1.01	1.00	1.01	1.01	1.00	1.01	1.12	1.01	0.79	102	74	0.08
26	9	2	12622	289992000	107.89	1.01	1.00	1.01	1.00	1.01	1.01	1.00	1.01	1.13	1.01	0.79	100	74	0.08
27	9	2	12622	289992000	111.84	1.01	1.01	1.01	1.00	1.01	1.01	1.00	1.01	1.14	1.01	0.78	100	74	0.08
28	9	2	12622	289992000	115.92	1.01	1.04	1.01	1.00	0.97	0.97	1.00	0.97	1.16	1.01	0.76	100	75	0.05
29	11	3	4919	149300000	2.44	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	107	65	0.91
30	11	3	4919	149300000	6.88	0.00	0.03	0.00	1.00	1.00	1.00	1.00	1.16	1.03	1.00	0.99	109	68	0.89
31	11	3	4919	149300000	11.03	0.11	0.06	0.11	1.00	1.76	1.76	1.00	1.77	1.09	1.00	0.98	109	73	0.85
32	11	3	4919	149300000	15.47	0.13	0.10	0.13	1.00	1.31	1.31	1.00	1.31	1.12	1.00	0.97	109	76	0.82
33	11	3	4919	149300000	19.91	0.15	0.13	0.15	1.00	1.18	1.18	0.86	1.01	1.11	1.00	0.96	109	75	0.79
34	11	3	4919	149300000	24.21	0.16	0.14	0.16	1.00	1.14	1.14	0.77	0.88	1.10	1.00	0.95	109	74	0.77
35	11	3	4919	149300000	28.65	0.16	0.17	0.16	1.00	0.99	0.99	1.36	1.35	1.10	1.00	0.94	109	73	0.75
36	11	3	4919	149300000	32.95	0.19	0.19	0.19	1.00	0.97	0.97	1.19	1.15	1.12	1.00	0.93	109	75	0.72
37	11	3	4919	149300000	37.39	0.26	0.22	0.26	1.00	1.19	1.19	1.15	1.36	1.13	1.00	0.92	109	76	0.69
38	11	3	4919	149300000	41.83	0.30	0.25	0.30	1.00	1.20	1.20	1.13	1.36	1.13	1.00	0.90	109	76	0.66
39	11	3	4919	149300000	46.13	0.30	0.29	0.30	1.00	1.02	1.02	1.29	1.31	1.14	1.00	0.89	109	77	0.62
40	11	3	4919	149300000	50.57	0.33	0.33	0.34	0.98	1.02	1.00	1.16	1.18	1.13	1.00	0.89	109	76	0.59
41	11	3	4919	149300000	54.87	0.37	0.36	0.37	1.00	1.02	1.02	1.23	1.25	1.12	1.00	0.89	109	75	0.55
42	11	3	4919	149300000	59.31	0.41	0.41	0.41	1.01	1.02	1.03	1.09	1.12	1.12	1.01	0.88	102	75	0.51
43	11	3	4919	149300000	63.47	0.45	0.44	0.45	1.00	1.02	1.02	1.01	1.04	1.12	1.01	0.87	102	75	0.47
44	11	3	4919	149300000	72.21	0.56	0.55	0.56	0.99	1.02	1.01	1.09	1.11	1.13	1.01	0.86	102	76	0.37
45	11	3	4919	149300000	76.50	0.63	0.62	0.64	0.99	1.02	1.01	1.04	1.06	1.12	1.01	0.84	102	75	0.30
46	11	3	4919	149300000	80.95	0.68	0.66	0.73	0.92	1.02	0.94	1.00	1.02	1.11	1.01	0.83	102	74	0.25
47	11	3	4919	149300000	85.24	0.82	0.72	0.82	1.00	1.14	1.14	0.95	1.08	1.11	1.01	0.82	102	73	0.19
48	11	3	4919	149300000	89.68	0.92	0.79	0.92	1.00	1.17	1.17	0.96	1.13	1.11	1.01	0.80	102	73	0.13
49	11	3	4919	149300000	94.13	0.94	0.80	0.94	1.00	1.19	1.19	1.03	1.23	1.12	1.01	0.79	102	74	0.12
50	11	3	4919	149300000	98.42	0.99	0.82	0.99	1.00	1.21	1.21	0.99	1.20	1.12	1.00	0.79	102	74	0.10

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
51	11	3	4919	149300000	102.87	1.00	0.84	1.00	1.00	1.19	1.19	1.00	1.18	1.12	1.00	0.78	102	74	0.07
52	9	2	31797	530000000	8.98	0.06	0.05	0.06	0.94	1.17	1.10	0.85	0.99	1.00	1.00	0.99	99	55	0.94
53	9	2	31797	530000000	13.86	0.08	0.06	0.09	0.90	1.43	1.29	0.96	1.38	1.00	1.00	0.96	99	55	0.94
54	9	2	31797	530000000	18.58	0.10	0.08	0.12	0.81	1.15	0.93	0.80	0.92	1.00	1.00	0.96	99	55	0.91
55	9	2	31797	530000000	23.46	0.13	0.13	0.15	0.90	1.04	0.93	1.30	1.35	1.00	1.00	0.96	99	55	0.87
56	9	2	31797	530000000	28.19	0.20	0.17	0.17	1.15	1.18	1.36	0.85	1.00	1.00	1.00	0.96	99	55	0.82
57	9	2	31797	530000000	33.07	0.25	0.17	0.20	1.26	1.48	1.86	0.75	1.11	1.00	1.00	0.95	99	55	0.82
58	9	2	31797	530000000	37.64	0.24	0.26	0.22	1.09	0.93	1.01	0.79	0.73	1.00	1.00	0.95	108	56	0.74
59	9	2	31797	530000000	42.36	0.31	0.28	0.26	1.21	1.10	1.33	0.93	1.02	1.00	1.00	0.94	108	56	0.71
60	9	2	31797	530000000	47.24	0.35	0.31	0.29	1.20	1.12	1.35	0.94	1.05	1.01	1.00	0.93	108	56	0.68
61	9	2	31797	530000000	56.85	0.41	0.39	0.33	1.24	1.05	1.31	0.97	1.02	1.03	1.00	0.92	108	57	0.60
62	9	2	31797	530000000	61.57	0.45	0.44	0.37	1.22	1.03	1.25	0.95	0.97	1.03	1.00	0.91	108	57	0.55
63	9	2	31797	530000000	76.06	0.83	0.66	0.81	1.03	1.26	1.30	0.86	1.08	1.02	1.04	0.91	108	59	0.33
64	9	2	31797	530000000	80.94	0.83	0.76	0.95	0.88	1.10	0.97	1.00	1.10	1.02	1.04	0.90	108	59	0.23
65	9	2	31797	530000000	85.67	1.02	0.81	1.03	0.99	1.26	1.25	0.90	1.14	1.02	1.07	0.89	108	59	0.18
66	9	2	31797	530000000	90.55	1.05	0.84	1.07	0.98	1.25	1.22	0.95	1.19	1.03	1.07	0.89	108	58	0.15
67	9	2	31797	530000000	95.12	1.07	0.86	1.07	1.00	1.24	1.24	0.97	1.20	1.05	1.07	0.89	108	58	0.13
68	9	2	31797	530000000	99.84	1.07	0.91	1.07	1.00	1.17	1.17	0.99	1.16	1.06	1.07	0.88	108	58	0.08
69	9	2	31797	530000000	104.72	1.07	0.93	1.07	1.00	1.15	1.15	0.99	1.14	1.06	1.07	0.87	108	58	0.06
70	9	2	31797	530000000	109.45	1.07	0.95	1.07	1.00	1.13	1.13	0.99	1.12	1.05	1.07	0.86	107	59	0.05
71	14	2	7707	153500000	5.18	0.01	0.03	0.03	0.40	0.34	0.14	1.47	0.49	1.00	1.00	1.00	99	55	0.92
72	14	2	7707	153500000	9.64	0.07	0.06	0.06	1.09	1.22	1.33	1.14	1.38	1.00	1.00	0.99	108	56	0.89
73	14	2	7707	153500000	13.81	0.10	0.09	0.11	0.96	1.09	1.05	1.57	1.71	1.00	1.00	0.99	108	56	0.85
74	14	2	7707	153500000	18.13	0.12	0.11	0.15	0.80	1.04	0.83	1.38	1.44	1.01	1.00	0.98	108	56	0.83
75	14	2	7707	153500000	22.59	0.12	0.14	0.18	0.66	0.85	0.56	1.38	1.18	1.01	1.00	0.98	108	57	0.81
76	14	2	7707	153500000	31.37	0.22	0.21	0.22	1.01	1.05	1.06	0.95	0.99	1.03	1.00	0.97	108	57	0.73

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
77	14	2	7707	153500000	35.68	0.26	0.24	0.26	0.98	1.08	1.06	1.14	1.23	1.03	1.00	0.96	108	59	0.71
78	14	2	7707	153500000	48.92	0.37	0.35	0.29	1.26	1.06	1.34	1.11	1.17	1.02	1.00	0.95	108	59	0.59
79	14	2	7707	153500000	53.38	0.37	0.40	0.34	1.10	0.93	1.02	1.11	1.03	1.02	1.00	0.95	108	59	0.55
80	14	2	7707	153500000	57.70	0.45	0.44	0.38	1.18	1.03	1.22	1.18	1.22	1.02	1.00	0.94	108	58	0.51
81	14	2	7707	153500000	62.16	0.49	0.48	0.43	1.15	1.03	1.18	1.08	1.11	1.03	1.00	0.94	108	58	0.47
82	14	2	7707	153500000	66.33	0.53	0.51	0.46	1.15	1.05	1.21	1.05	1.11	1.05	1.00	0.94	108	58	0.44
83	14	2	7707	153500000	70.65	0.58	0.53	0.51	1.13	1.10	1.24	1.08	1.19	1.06	1.01	0.93	108	58	0.42
84	14	2	7707	153500000	75.11	0.63	0.58	0.54	1.16	1.09	1.26	1.06	1.15	1.06	1.00	0.92	107	59	0.37
85	14	2	7707	153500000	79.42	0.70	0.63	0.61	1.15	1.12	1.29	1.01	1.13	1.05	1.01	0.91	107	61	0.32
86	14	2	7707	153500000	83.88	0.76	0.71	0.66	1.15	1.08	1.24	0.93	1.00	1.05	1.01	0.90	107	62	0.24
87	14	2	7707	153500000	88.20	0.84	0.76	0.72	1.16	1.10	1.28	0.90	1.00	1.05	1.01	0.89	107	62	0.19
88	14	2	7707	153500000	92.66	0.87	0.80	0.79	1.09	1.08	1.18	0.87	0.94	1.06	1.01	0.88	107	61	0.14
89	14	2	7707	153500000	97.12	0.92	0.84	0.87	1.06	1.09	1.16	0.97	1.06	1.06	1.01	0.87	107	61	0.10
90	14	2	7707	153500000	101.44	0.99	0.87	0.91	1.08	1.14	1.23	0.95	1.09	1.06	1.02	0.86	107	61	0.08
91	14	2	7707	153500000	105.90	1.01	0.94	1.01	1.00	1.07	1.07	0.95	1.01	1.07	1.02	0.86	107	62	0.01
92	14	3	10087	216000000	17.89	0.10	0.10	0.10	1.00	1.01	1.01	0.88	0.89	0.99	1.00	1.00	108	58	0.63
93	14	3	10087	216000000	22.03	0.10	0.12	0.10	1.00	0.88	0.88	0.88	0.78	0.99	1.00	0.99	108	58	0.61
94	14	3	10087	216000000	26.03	0.21	0.14	0.21	1.00	1.53	1.53	0.97	1.48	0.99	1.00	0.99	108	58	0.60
95	14	3	10087	216000000	30.17	0.24	0.17	0.24	1.00	1.41	1.41	0.95	1.34	1.00	1.00	0.98	107	59	0.56
96	14	3	10087	216000000	34.05	0.28	0.20	0.28	1.00	1.37	1.37	0.82	1.13	1.02	1.00	0.98	107	61	0.53
97	14	3	10087	216000000	38.05	0.32	0.23	0.32	1.00	1.40	1.40	0.90	1.25	1.03	1.00	0.97	107	62	0.50
98	14	3	10087	216000000	42.19	0.36	0.26	0.36	1.00	1.36	1.36	0.92	1.26	1.03	1.00	0.96	107	62	0.47
99	14	3	10087	216000000	46.19	0.38	0.30	0.38	1.00	1.26	1.26	0.97	1.22	1.02	1.00	0.96	107	61	0.43
100	14	3	10087	216000000	50.33	0.46	0.35	0.46	1.00	1.34	1.34	0.90	1.20	1.02	1.00	0.94	107	61	0.39
101	14	3	10087	216000000	54.34	0.50	0.38	0.50	1.00	1.34	1.34	0.88	1.18	1.02	1.00	0.94	107	61	0.36
102	14	3	10087	216000000	58.48	0.58	0.40	0.56	1.03	1.46	1.50	0.82	1.20	1.03	1.00	0.93	107	62	0.33

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
103	14	3	10087	216000000	62.62	0.60	0.43	0.61	0.98	1.40	1.37	0.87	1.22	1.03	1.00	0.92	107	62	0.30
104	14	3	10087	216000000	66.62	0.65	0.47	0.67	0.97	1.38	1.34	0.87	1.20	1.03	1.00	0.91	107	62	0.26
105	14	3	10087	216000000	70.76	0.73	0.50	0.71	1.03	1.44	1.48	0.84	1.22	1.04	1.00	0.91	107	63	0.23
106	14	3	10087	216000000	74.77	0.78	0.55	0.79	0.98	1.40	1.37	0.84	1.18	1.06	1.00	0.91	107	65	0.18
107	14	3	10087	216000000	78.91	0.83	0.58	0.85	0.98	1.45	1.42	0.84	1.22	1.09	1.00	0.91	109	68	0.16
108	14	3	10087	216000000	82.78	0.87	0.61	0.89	0.98	1.44	1.41	0.84	1.21	1.15	1.00	0.90	109	73	0.13
109	14	3	10087	216000000	86.92	0.93	0.61	0.91	1.02	1.51	1.54	0.83	1.25	1.19	1.00	0.89	109	76	0.12
110	14	3	10087	216000000	91.05	0.93	0.63	0.93	1.00	1.48	1.48	0.82	1.22	1.18	1.00	0.88	109	75	0.10
111	14	3	10087	216000000	95.06	0.93	0.64	0.94	0.99	1.44	1.43	0.86	1.24	1.17	1.00	0.86	109	74	0.09
112	14	3	10087	216000000	99.20	0.97	0.66	0.98	0.99	1.48	1.47	0.82	1.22	1.16	1.00	0.86	109	73	0.08
113	14	3	10087	216000000	103.20	0.99	0.67	1.00	0.99	1.48	1.47	0.82	1.22	1.18	1.00	0.85	109	75	0.06
114	14	3	10087	216000000	107.34	1.00	0.68	1.00	1.00	1.47	1.47	0.81	1.19	1.20	1.00	0.84	109	76	0.05
115	14	3	10087	216000000	111.48	1.00	0.69	1.00	1.00	1.45	1.45	0.82	1.18	1.20	1.00	0.82	109	76	0.04
116	14	3	10087	216000000	115.49	0.87	0.69	0.87	1.00	1.25	1.25	0.94	1.18	1.20	0.87	0.81	109	77	0.04
117	14	3	10087	216000000	119.63	0.82	0.69	0.86	0.95	1.18	1.12	1.06	1.25	1.20	0.87	0.81	109	76	0.04
118	10	1	3479	85714286	10.70	0.05	0.00	0.05	1.00	1.00	1.00	0.00	1.00	1.01	1.00	0.99	107	61	0.88
119	10	1	3479	85714286	16.42	0.12	0.05	0.12	1.01	2.33	2.35	0.00	1.00	1.01	1.00	0.98	107	61	0.83
120	10	1	3479	85714286	22.14	0.20	0.09	0.20	1.00	2.18	2.18	0.61	1.32	1.01	1.00	0.96	107	62	0.79
121	10	1	3479	85714286	27.68	0.26	0.16	0.26	1.00	1.60	1.60	0.77	1.23	1.01	1.00	0.96	107	62	0.72
122	10	1	3479	85714286	33.39	0.29	0.21	0.30	0.98	1.36	1.33	0.69	0.94	1.02	1.00	0.96	107	62	0.67
123	10	1	3479	85714286	38.93	0.33	0.25	0.34	0.98	1.32	1.29	0.60	0.79	1.04	1.00	0.96	107	63	0.63
124	10	1	3479	85714286	44.65	0.36	0.28	0.38	0.95	1.32	1.25	0.80	1.05	1.08	1.00	0.95	107	65	0.60
125	10	1	3479	85714286	50.00	0.44	0.28	0.46	0.95	1.54	1.46	0.73	1.13	1.13	1.00	0.93	109	68	0.59
126	10	1	3479	85714286	55.72	0.50	0.32	0.56	0.89	1.55	1.38	0.64	0.99	1.17	1.00	0.92	109	73	0.55
127	10	1	3479	85714286	61.44	0.58	0.37	0.66	0.88	1.57	1.38	0.55	0.86	1.16	1.00	0.91	109	76	0.50
128	10	1	3479	85714286	66.97	0.68	0.45	0.80	0.85	1.51	1.28	0.77	1.17	1.15	1.00	0.89	109	75	0.42

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
129	10	1	3479	85714286	72.69	0.74	0.51	0.84	0.88	1.46	1.28	0.71	1.04	1.14	1.00	0.88	109	74	0.37
130	10	1	3479	85714286	78.23	0.84	0.55	0.88	0.95	1.51	1.43	0.74	1.12	1.16	1.00	0.87	109	73	0.32
131	10	1	3479	85714286	83.95	0.89	0.61	0.91	0.98	1.45	1.42	0.70	1.01	1.18	1.00	0.85	109	75	0.26
132	10	1	3479	85714286	89.67	0.94	0.64	0.95	0.98	1.45	1.42	0.80	1.16	1.18	1.00	0.83	109	76	0.23
133	10	1	3479	85714286	95.20	0.96	0.71	0.97	0.99	1.37	1.36	0.78	1.06	1.19	1.00	0.82	109	76	0.17
134	10	1	3479	85714286	100.92	0.99	0.75	1.00	0.99	1.32	1.31	0.82	1.08	1.18	1.00	0.82	109	77	0.12
135	11	4	6352	202241810	3.37	0.02	0.00	0.02	1.00	1.00	1.00	0.00	0.00	1.00	1.00	0.97	109	76	1.00
136	11	4	6352	202241810	7.55	0.03	0.03	0.03	1.00	0.76	0.76	0.00	0.00	0.99	1.00	0.96	109	75	0.97
137	11	4	6352	202241810	11.59	0.06	0.06	0.08	0.69	1.00	0.69	0.00	0.00	0.99	1.00	0.95	109	74	0.95
138	11	4	6352	202241810	15.77	0.11	0.09	0.14	0.81	1.19	0.96	0.49	0.58	0.98	1.00	0.95	109	73	0.91
139	11	4	6352	202241810	19.81	0.17	0.13	0.18	0.92	1.25	1.15	0.67	0.83	1.00	1.00	0.94	109	75	0.85
140	11	4	6352	202241810	23.99	0.19	0.17	0.20	0.96	1.16	1.11	0.57	0.66	1.01	1.00	0.92	109	76	0.82
141	11	4	6352	202241810	28.17	0.21	0.20	0.22	0.98	1.06	1.04	0.87	0.93	1.01	1.00	0.91	109	76	0.79
142	11	4	6352	202241810	32.21	0.24	0.23	0.24	1.00	1.04	1.04	0.76	0.80	1.01	1.00	0.90	109	77	0.75
143	11	4	6352	202241810	36.39	0.26	0.26	0.27	0.96	1.03	0.99	0.86	0.88	1.01	1.03	0.90	109	76	0.73
144	11	4	6352	202241810	40.43	0.31	0.31	0.31	1.00	1.00	1.00	0.88	0.87	1.00	1.03	0.90	109	75	0.68
145	11	4	6352	202241810	44.61	0.33	0.35	0.33	1.00	0.95	0.95	0.92	0.87	1.00	1.03	0.89	102	75	0.63
146	11	4	6352	202241810	48.52	0.36	0.36	0.36	1.00	0.99	0.99	0.93	0.92	1.00	1.03	0.88	102	75	0.62
147	11	4	6352	202241810	56.74	0.42	0.41	0.42	1.00	1.02	1.02	0.89	0.91	1.01	1.03	0.87	102	76	0.58
148	11	4	6352	202241810	60.78	0.45	0.44	0.45	1.01	1.03	1.04	0.91	0.94	1.00	1.03	0.86	102	75	0.55
149	11	4	6352	202241810	64.96	0.50	0.47	0.48	1.04	1.06	1.10	0.90	0.96	0.99	1.03	0.84	102	74	0.51
150	11	4	6352	202241810	69.00	0.55	0.49	0.52	1.05	1.11	1.17	0.89	0.99	0.99	1.03	0.83	102	73	0.49
151	11	4	6352	202241810	73.18	0.57	0.53	0.56	1.02	1.07	1.09	0.87	0.93	0.99	1.03	0.82	102	73	0.45
152	11	4	6352	202241810	77.36	0.62	0.59	0.62	1.00	1.04	1.04	0.93	0.96	1.00	1.03	0.81	102	74	0.39
153	11	4	6352	202241810	81.40	0.72	0.64	0.72	1.00	1.13	1.13	0.85	0.96	1.00	1.07	0.80	102	74	0.35
154	11	4	6352	202241810	85.58	0.80	0.71	0.81	0.99	1.13	1.12	0.85	0.96	1.00	1.07	0.80	102	74	0.28

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
155	11	4	6352	202241810	89.62	0.88	0.77	0.89	0.99	1.15	1.14	0.83	0.96	1.00	1.07	0.79	102	74	0.22
156	11	4	6352	202241810	93.80	0.94	0.80	0.93	1.01	1.18	1.19	0.84	0.99	1.00	1.07	0.79	102	74	0.19
157	11	4	6352	202241810	97.71	0.97	0.82	0.97	1.00	1.19	1.19	0.87	1.04	1.00	1.07	0.78	102	74	0.17
158	11	4	6352	202241810	101.75	1.02	0.85	1.02	1.00	1.19	1.19	0.88	1.06	1.02	1.07	0.77	102	75	0.13
159	11	4	6352	202241810	105.93	1.05	0.85	1.05	1.00	1.24	1.24	0.89	1.10	1.04	1.07	0.76	102	76	0.13
160	11	4	6352	202241810	109.97	1.07	0.92	1.07	1.00	1.17	1.17	0.89	1.03	1.07	1.07	0.75	103	78	0.07
161	11	4	6352	202241810	114.15	1.07	0.93	1.07	1.00	1.15	1.15	0.89	1.03	1.08	1.07	0.73	103	81	0.06
162	11	4	6352	202241810	118.19	1.07	0.95	1.07	1.00	1.13	1.13	0.91	1.03	1.08	1.07	0.72	111	82	0.04
163	11	4	6352	202241810	122.37	1.03	0.96	1.03	1.00	1.08	1.08	0.95	1.03	1.08	1.03	0.71	111	82	0.03
164	11	4	6352	202241810	126.55	1.03	0.96	1.03	1.00	1.07	1.07	0.97	1.05	1.08	1.03	0.70	111	82	0.02
165	11	2	4774	145377589	12.09	0.06	0.03	0.06	1.00	1.82	1.82	0.00	0.00	1.02	1.00	0.99	102	76	0.89
166	11	2	4774	145377589	15.87	0.13	0.07	0.13	1.00	1.90	1.90	0.96	1.82	1.01	1.00	0.98	109	73	0.85
167	11	2	4774	145377589	19.54	0.15	0.13	0.15	1.00	1.21	1.21	1.06	1.29	1.03	1.00	0.98	109	76	0.79
168	11	2	4774	145377589	23.32	0.18	0.15	0.18	1.00	1.18	1.18	1.12	1.32	1.04	1.00	0.96	109	75	0.76
169	11	2	4774	145377589	27.11	0.18	0.18	0.18	1.00	1.03	1.03	1.56	1.61	1.04	1.01	0.95	109	74	0.74
170	11	2	4774	145377589	30.77	0.28	0.22	0.27	1.01	1.28	1.29	1.03	1.32	1.04	1.01	0.94	109	73	0.70
171	11	2	4774	145377589	34.55	0.32	0.26	0.32	0.99	1.23	1.22	1.03	1.26	1.04	1.01	0.94	109	75	0.66
172	11	2	4774	145377589	38.22	0.36	0.30	0.36	1.00	1.21	1.21	1.02	1.25	1.03	1.01	0.94	109	76	0.62
173	11	2	4774	145377589	42.00	0.41	0.35	0.41	1.01	1.18	1.19	0.89	1.06	1.03	1.01	0.93	109	76	0.57
174	11	2	4774	145377589	45.54	0.41	0.38	0.41	1.01	1.09	1.10	0.89	0.97	1.03	1.01	0.92	109	77	0.54
175	11	2	4774	145377589	52.99	0.51	0.46	0.52	0.99	1.11	1.10	0.90	0.99	1.04	1.01	0.91	109	76	0.45
176	11	2	4774	145377589	56.65	0.54	0.48	0.57	0.95	1.13	1.07	0.85	0.96	1.03	1.01	0.90	109	75	0.44
177	11	2	4774	145377589	60.44	0.59	0.53	0.61	0.96	1.10	1.06	0.89	0.98	1.02	1.01	0.89	102	75	0.38
178	11	2	4774	145377589	64.10	0.64	0.57	0.66	0.98	1.12	1.10	0.81	0.91	1.02	1.01	0.88	102	75	0.34
179	11	2	4774	145377589	67.89	0.69	0.62	0.71	0.98	1.11	1.09	0.90	1.00	1.02	1.01	0.87	102	76	0.30
180	11	2	4774	145377589	71.67	0.74	0.65	0.75	0.98	1.12	1.10	0.85	0.95	1.03	1.01	0.86	102	75	0.26

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
181	11	2	4774	145377589	75.34	0.73	0.69	0.75	0.98	1.07	1.05	0.85	0.91	1.03	0.96	0.85	102	74	0.23
182	11	2	4774	145377589	79.12	0.80	0.74	0.78	1.02	1.08	1.10	0.91	0.98	1.03	0.96	0.85	102	73	0.18
183	11	2	4774	145377589	82.78	0.83	0.76	0.85	0.98	1.09	1.07	0.99	1.08	1.03	0.96	0.84	102	73	0.16
184	11	2	4774	145377589	86.57	0.87	0.80	0.88	0.99	1.09	1.08	0.99	1.08	1.03	0.96	0.84	102	74	0.12
185	11	2	4774	145377589	90.11	0.89	0.81	0.89	1.00	1.10	1.10	1.01	1.11	1.04	0.96	0.84	102	74	0.10
186	11	2	4774	145377589	93.77	0.91	0.85	0.91	1.00	1.08	1.08	1.03	1.11	1.05	0.96	0.83	102	74	0.07
187	11	2	4774	145377589	97.56	0.93	0.83	0.93	1.00	1.13	1.13	1.01	1.14	1.07	0.96	0.81	102	74	0.09
188	11	2	4774	145377589	101.22	0.95	0.88	0.95	1.00	1.08	1.08	0.99	1.07	1.10	0.96	0.80	102	74	0.04
189	11	2	4774	145377589	105.01	0.96	0.89	0.96	1.00	1.09	1.09	0.98	1.06	1.11	0.96	0.79	102	74	0.03
190	11	2	4774	145377589	108.67	0.96	0.89	0.96	1.00	1.08	1.08	0.98	1.06	1.11	0.96	0.78	102	75	0.03
191	8	2	7289	190844707	8.43	0.02	0.00	0.03	0.67	1.00	0.67	0.00	0.00	1.00	1.00	0.97	102	73	0.84
192	8	2	7289	190844707	14.23	0.10	0.01	0.10	0.96	1.00	0.96	0.00	0.00	1.00	1.00	0.95	102	74	0.83
193	8	2	7289	190844707	20.04	0.14	0.03	0.15	0.93	1.00	0.93	0.62	1.00	1.01	1.00	0.93	102	74	0.81
194	8	2	7289	190844707	25.66	0.25	0.13	0.26	0.96	1.98	1.90	0.80	1.58	1.01	1.00	0.92	102	74	0.72
195	8	2	7289	190844707	31.46	0.28	0.18	0.28	0.99	1.60	1.58	0.85	1.35	1.01	1.00	0.92	102	74	0.67
196	8	2	7289	190844707	37.08	0.34	0.24	0.34	0.98	1.39	1.36	0.83	1.16	1.01	1.00	0.91	102	74	0.60
197	8	2	7289	190844707	42.88	0.39	0.29	0.40	0.99	1.35	1.34	0.88	1.19	1.01	1.00	0.91	102	74	0.55
198	8	2	7289	190844707	48.31	0.44	0.37	0.44	0.99	1.19	1.18	0.92	1.09	1.02	1.00	0.90	102	75	0.47
199	8	2	7289	190844707	53.93	0.49	0.43	0.49	0.99	1.14	1.13	0.96	1.09	1.03	1.00	0.88	102	76	0.42
200	8	2	7289	190844707	59.74	0.55	0.47	0.57	0.98	1.19	1.17	0.92	1.10	1.05	1.00	0.87	103	78	0.38
201	8	2	7289	190844707	65.36	0.61	0.52	0.64	0.96	1.19	1.14	0.90	1.06	1.08	1.03	0.85	103	81	0.32
202	8	2	7289	190844707	71.16	0.66	0.57	0.69	0.96	1.17	1.12	0.90	1.05	1.09	1.03	0.83	103	82	0.28
203	8	2	7289	190844707	76.78	0.70	0.62	0.74	0.95	1.13	1.07	0.85	0.96	1.09	1.03	0.81	111	82	0.22
204	8	2	7289	190844707	82.58	0.73	0.66	0.78	0.94	1.11	1.04	0.91	1.01	1.09	1.03	0.80	111	82	0.18
205	8	2	7289	190844707	88.39	0.75	0.72	0.80	0.94	1.05	0.99	0.94	0.99	1.10	1.03	0.78	111	83	0.12
206	8	2	7289	190844707	94.01	0.81	0.75	0.85	0.96	1.08	1.04	0.93	1.00	1.11	0.91	0.78	85	84	0.09

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
207	8	2	7289	190844707	99.81	0.85	0.78	0.89	0.96	1.09	1.05	0.89	0.96	1.11	0.91	0.77	85	84	0.06
208	8	2	7289	190844707	105.43	0.89	0.81	0.92	0.97	1.10	1.07	0.85	0.93	1.12	0.92	0.75	85	84	0.03
209	8	2	7289	190844707	111.24	0.91	0.84	0.92	0.99	1.08	1.07	0.90	0.97	1.12	0.92	0.75	102	85	0.01
210	7	2	3094	102500000	17.48	0.19	0.09	0.12	1.62	2.11	3.42	0.69	1.46	1.00	1.00	0.97	102	74	0.84
211	7	2	3094	102500000	23.50	0.27	0.18	0.19	1.39	1.50	2.09	0.79	1.19	1.00	1.00	0.96	102	74	0.75
212	7	2	3094	102500000	29.13	0.30	0.22	0.22	1.35	1.34	1.81	0.96	1.29	1.01	1.00	0.95	102	74	0.70
213	7	2	3094	102500000	34.95	0.35	0.26	0.26	1.33	1.32	1.76	1.01	1.33	1.02	1.00	0.94	102	74	0.66
214	7	2	3094	102500000	40.97	0.39	0.23	0.30	1.33	1.74	2.31	0.99	1.73	1.04	1.00	0.92	102	75	0.70
215	7	2	3094	102500000	46.80	0.44	0.36	0.35	1.26	1.22	1.54	0.97	1.18	1.07	1.00	0.90	102	76	0.56
216	7	2	3094	102500000	52.82	0.49	0.40	0.40	1.23	1.23	1.51	0.87	1.07	1.08	1.00	0.88	103	78	0.52
217	7	2	3094	102500000	58.64	0.55	0.45	0.47	1.19	1.24	1.48	0.85	1.05	1.08	1.00	0.86	103	81	0.48
218	7	2	3094	102500000	64.66	0.59	0.49	0.55	1.08	1.21	1.31	0.85	1.03	1.08	1.00	0.85	103	82	0.43
219	7	2	3094	102500000	70.68	0.65	0.52	0.63	1.03	1.26	1.30	0.84	1.06	1.09	1.00	0.83	111	82	0.41
220	7	2	3094	102500000	76.50	0.74	0.63	0.71	1.05	1.18	1.24	0.94	1.11	1.10	1.00	0.83	111	82	0.30
221	7	2	3094	102500000	82.52	0.82	0.71	0.83	0.99	1.16	1.15	0.85	0.98	1.10	1.00	0.81	111	83	0.22
222	7	2	3094	102500000	88.35	0.87	0.73	0.91	0.95	1.18	1.12	0.86	1.02	1.10	1.00	0.80	85	84	0.19
223	7	2	3094	102500000	94.37	0.95	0.77	0.95	1.00	1.24	1.24	0.90	1.11	1.10	1.00	0.79	85	84	0.16
224	7	2	3094	102500000	100.00	0.98	0.78	0.98	1.00	1.26	1.26	0.87	1.10	1.11	1.00	0.78	102	86	0.15
225	7	2	3094	102500000	105.83	1.00	0.84	1.00	1.00	1.18	1.18	0.92	1.08	1.13	1.00	0.76	102	88	0.08

APPENDIX D

No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	Y
1	11	2	4774	145377589	12.09	0.06	0.03	0.06	1.00	1.82	1.82	0.00	0.00	1.02	1.00	0.99	102	76	0.89
2	11	2	4774	145377589	15.87	0.13	0.07	0.13	1.00	1.90	1.90	0.96	1.82	1.01	1.00	0.98	109	73	0.85
3	11	2	4774	145377589	19.54	0.15	0.13	0.15	1.00	1.21	1.21	1.06	1.29	1.03	1.00	0.98	109	76	0.79
4	11	2	4774	145377589	23.32	0.18	0.15	0.18	1.00	1.18	1.18	1.12	1.32	1.04	1.00	0.96	109	75	0.76
5	11	2	4774	145377589	27.11	0.18	0.18	0.18	1.00	1.03	1.03	1.56	1.61	1.04	1.01	0.95	109	74	0.74
6	11	2	4774	145377589	30.77	0.28	0.22	0.27	1.01	1.28	1.29	1.03	1.32	1.04	1.01	0.94	109	73	0.70
7	11	2	4774	145377589	34.55	0.32	0.26	0.32	0.99	1.23	1.22	1.03	1.26	1.04	1.01	0.94	109	75	0.66
8	11	2	4774	145377589	38.22	0.36	0.30	0.36	1.00	1.21	1.21	1.02	1.25	1.03	1.01	0.94	109	76	0.62
9	11	2	4774	145377589	42.00	0.41	0.35	0.41	1.01	1.18	1.19	0.89	1.06	1.03	1.01	0.93	109	76	0.57
10	11	2	4774	145377589	45.54	0.41	0.38	0.41	1.01	1.09	1.10	0.89	0.97	1.03	1.01	0.92	109	77	0.54
11	11	2	4774	145377589	52.99	0.51	0.46	0.52	0.99	1.11	1.10	0.90	0.99	1.04	1.01	0.91	109	76	0.45
12	11	2	4774	145377589	56.65	0.54	0.48	0.57	0.95	1.13	1.07	0.85	0.96	1.03	1.01	0.90	109	75	0.44
13	11	2	4774	145377589	60.44	0.59	0.53	0.61	0.96	1.10	1.06	0.89	0.98	1.02	1.01	0.89	102	75	0.38
14	11	2	4774	145377589	64.10	0.64	0.57	0.66	0.98	1.12	1.10	0.81	0.91	1.02	1.01	0.88	102	75	0.34
15	11	2	4774	145377589	67.89	0.69	0.62	0.71	0.98	1.11	1.09	0.90	1.00	1.02	1.01	0.87	102	76	0.30
16	11	2	4774	145377589	71.67	0.74	0.65	0.75	0.98	1.12	1.10	0.85	0.95	1.03	1.01	0.86	102	75	0.26
17	11	2	4774	145377589	75.34	0.73	0.69	0.75	0.98	1.07	1.05	0.85	0.91	1.03	0.96	0.85	102	74	0.23
18	11	2	4774	145377589	79.12	0.80	0.74	0.78	1.02	1.08	1.10	0.91	0.98	1.03	0.96	0.85	102	73	0.18
19	11	2	4774	145377589	82.78	0.83	0.76	0.85	0.98	1.09	1.07	0.99	1.08	1.03	0.96	0.84	102	73	0.16
20	11	2	4774	145377589	86.57	0.87	0.80	0.88	0.99	1.09	1.08	0.99	1.08	1.03	0.96	0.84	102	74	0.12
21	11	2	4774	145377589	90.11	0.89	0.81	0.89	1.00	1.10	1.10	1.01	1.11	1.04	0.96	0.84	102	74	0.10
22	11	2	4774	145377589	93.77	0.91	0.85	0.91	1.00	1.08	1.08	1.03	1.11	1.05	0.96	0.83	102	74	0.07
23	11	2	4774	145377589	97.56	0.93	0.83	0.93	1.00	1.13	1.13	1.01	1.14	1.07	0.96	0.81	102	74	0.09
24	11	2	4774	145377589	101.22	0.95	0.88	0.95	1.00	1.08	1.08	0.99	1.07	1.10	0.96	0.80	102	74	0.04
25	11	2	4774	145377589	105.01	0.96	0.89	0.96	1.00	1.09	1.09	0.98	1.06	1.11	0.96	0.79	102	74	0.03
26	11	2	4774	145377589	108.67	0.96	0.89	0.96	1.00	1.08	1.08	0.98	1.06	1.11	0.96	0.78	102	75	0.03