Received on: 08 September 2023 **Revised on: 23 November 2023** **Accepted: 20 January 2024**

RESEARCH ARTICLE
DOI: 10.47703/ejebs.v68i1.331

Artificial Intelligence Models for Predicting Budget Expenditures

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For citation: Capone, C., Talgat, S., Hazir, O., Abdrashova, K. & Kozhakhmetova, A. (2024). Artificial Intelligence Models for Predicting Budget Expenditures Eurasian Journal of Economic and Business Studies, 68(1), 32-43.

Conflict of interest: author(s) declare that there is no conflict of interest.

EJEBS

Abstract

This study develops and tests a machine learning (ML)-based cost forecasting model against traditional earned value management (EVM) techniques. Utilizing Python for ML implementation, the research applies algorithms to a dataset of completed projects globally, evaluating their performance with metrics like mean absolute percentage error (MAPE) and percentage error (PE). The results confirmed that ML give more accurate results than the traditional methods. Thus, the initial rate showing that XGBoost is more accurate than the traditional method using Index-2 is 88%. In 23 of 25 randomly selected projects, this algorithm was more accurate. At the middle stage, the same frequency is 92.6%; later stage, the selected criterion further confirms that the ML algorithm is more accurate than the traditional method, accounting for 75% of 21 projects out of 28. By introducing ML into project management forecasting, managers could spend less time on the technical tasks in their projects. Despite its effectiveness, the study's scope is limited by a small sample size of 110 projects and the testing of only three algorithms. Future research is suggested to expand the dataset and explore additional algorithms, including neural networks and tree-based methods, to enhance forecasting precision.

Keywords: Economics, Business, Project Management, Cost Forecasting, Earned Value Method, Artificial Intelligence, Machine Learning, Machine Learning Models, Python

SCSTI: 06.54.31

JEL Code: M10, M15, O22

Financial support: The study was carried out within the framework of funding by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP19680313)

1. INTRODUCTION

Despite the growing body of knowledge and best practices in the Project Management (PM) field both globally (Alvarez-Dionisi, 2015; Derici, 2019) and in Kazakhstan (Narbaev, 2015), rising expenditures and project failures continue to be a common issue. Globally, more than 67% of projects suffer from such cost overruns, and about 12% of investments in infrastructure projects are wasted due to inappropriate use of PM techniques.

There are a lot of underestimated or even overlooked cost items in projects, but they can lead to various financial and business problems later. For instance, in the course of project realization there are various types of costs; some of them are direct (they can be easily related to product manufacture or service offer on the project), others are indirect costs, not directly related to product manufacture or service offer, but indirectly related to project execution (Anicic, 2019). Project managers, in cooperation with financial experts, do the estimation of these costs and benefits for better management of projects. Because a proper model of cost forecasting may help to avoid project risks. Moreover, considering that many projects do not develop according to plans, new ways of cost estimates are necessary, with the aim of finding alternative solutions.

For instance, in Kazakhstan, over 60% of infrastructure projects are delivered with cost overruns (Tsekhovoy, 2010). Moreover, managers may receive considerable information during projects, leading to slowdowns in decision-making (Barber, 2021). Therefore, new models are being invented and implemented that will make it possible to predict the project budget with a low percentage of errors and minimal losses, and even better, work much faster and more efficiently, which will help project managers reduce the time for calculations. In such conditions, artificial intelligence (AI) technology can simplify and speed up work (Dacre, 2020). AI can be defined as the machines that are created to simulate human intelligence to do and learn as a brain of human do (Mentzas, 1994).

Artificial intelligence is a reality in our days getting more and more relevancy. Therefore, it should be explored both scientifically and business wise (Bento et al., 2022). Implementing AI in the project management field will help in a wide range of missions and tasks, such as increasing automation, productivity, help in making intelligent decisions, solving complex problems, managing repetitive missions and tasks, enhancing lifestyle, and assisting in complex analysis (Jiang et al., 2017; Ribeiro et al., 2021). The varieties of AI applications and tools enable better project performance as well as enhance the efficiency of the project management implementation (Elkhatib et al., 2022).

AI has great potential that cannot be ignored because its application contributes to more accurate budget forecasting and overall increased project efficiency, thereby ensuring organizational growth (Kyläheiko et al., 2017). Therefore, to solve the problems in PM, more advanced and complex AI approaches are increasingly being applied, such as ML techniques (Haenlein & Kaplan, 2019), which are used by every second application or website worldwide.

To date, despite the unconditional relevance of this area, a limited number of studies have been conducted that used ML approaches in PM. Therefore, this paper aims to develop a new project completion budget forecasting model using ML algorithms to address the above research gap.

The structure of the study consists of the following stages: at the initial stage, an analysis of previous literature was carried out; a database of 110 real projects from all over the world has been created; and 2 algorithms were analyzed to predict the cost of a project upon completion ML. As a result, a model was developed in the Python programming language and conclusions and recommendations for further research were drawn up.

2. LITERATURE REVIEW

This section considers the theory of cost forecasting models, the concept of AI and its application for Predicting Budget Expenditures. Project costs management is a process necessary for project realization within certain budget which includes cost management planning, cost estimation, budget setting and cost control (PMI, 2007). The forecasting models vary for different data set. Moreover, Fildes and Lusk (1984) stated that no forecaster could be the 'best' method from the various forecasting competitions. All forecasting methods have distinct advantages and disadvantages. Therefore, selecting the proper forecasting method is critical to all decision-makers.

Ma et al. (2023) conducted an exploratory review and found that frequently used forecasting models are traditional forecasting, hybrid methods, and AI tool – machine learning algorithm. While traditional methods like time series analysis, hedonic price model and regression analysis may allow for standard deviations and take time, AI tools are more trustworthy due to more accurate and faster calculations. In addition, AI is observed as an effective forecasting method by PM managers. That's why this study is focused on using AI for making more valid and reliable forecasting of chosen projects.

AI was defined as a set of machines that can perform multi-tasks in intelligent ways by adapting to several situations (Mahmood et al., 2023). Ju et al. (2020) stated that AI positively impacts company performance. But the literature analysis found that the application of AI is not so widespread in companies and especially not in all of project management areas (Bento et al., 2022). Ong and Uddin (2020) note that with the new era of data, the application of AI will be significantly expanded.

The literature review founds the different directions of studies related to using AI in PM like benefits of AI in project management (García et al., 2017), project duration forecasting (Wauters and Vanhoucke, 2016), the development of strategic roadmaps and their implementation supported by project management (Kerr and Phaal, 2017), the potential of using AI to improve processes and optimize strategies in various fields (Elmousalami, 2020), applying ML to predict project duration (Pellerin & Perrier, 2019) and costs (Kim, 2015).

After reviewing the general concepts of AI in PM, articles (Chou et al., 2010) move on to a more specialized topic that explores AI methods and models for accurately estimating project costs and optimizing costs. For example, Fridgeirsson et al.(2021) explored the role of AI in improving cost management according to PMI's Project Management Body of Knowledge. The panel determined that AI will significantly impact not only cost, also schedule, and risk management in the future through the use of historical data for estimating and planning. Still, it will likely not have the same impact in areas that require human leadership skills and interpersonal interactions.

A study by Alhares et al. (2019) examines the application of coupled intelligent models to improve project completion forecasting in the construction industry. The researchers used a two-step approach, combining global harmony and brute force algorithms with an extreme learning machine to make more reliable predictions. The results show that the proposed models provide improved cost forecasting accuracy, which helps project managers make informed decisions and improve control.

The article by Chou et al. (2015) discusses applications of AI, including multiple regression analysis, artificial neural networks, case-based reasoning, and a new hybrid approach. In the first case, the authors use a hybrid approach to estimate the development costs of liquid crystal display manufacturing equipment, highlighting cost control and decision-making improvements. The second paper uses case-based reasoning with genetic algorithm integration to predict bid amounts for bridge construction projects. In two studies, the authors use accurate data and apply a crossvalidation method to evaluate the performance and accuracy of the models. The results confirm that AI-based hybrid models, especially those using artificial neural networks and genetic algorithms, demonstrate high efficiency and accuracy in predicting bid amounts, which can help contractors make informed bidding decisions in the bridge construction industry.

In turn, Kazakh authors who used AI approaches, particularly ML methods in PM, conducted a limited number of studies. For example, Narbaev and De Marco (2017) improved statistically based EAC ($) cost forecasting by integrating risk patterns. Algiev (2012) proposed a PM-based framework for public projects to predict their success using qualitative research but limited themselves to practical recommendations.

The general trend of these studies emphasizes that AI is becoming an integral part of modern business and PM. Process optimization, cost forecasting, risk management, and efficiency improvements are becoming more accessible and accurate using modern AI methods and models.

3. METHODOLOGY

3.1 Data collection

This study used the data of 110 projects from various fields, which were collected and published by the Operations Research & Schedule team. Only data such as Actual Cost (AC), Planned Cost (PV), Earned Value (EV), and projects with tracking period information were included in the collected database because the absence of tracking periods indicates that work was not performed.

3.2 Data processing

MS Excel software analysis

Initially, the database was generated and divided into intermediate stages on the MS Excel platform. Afterwards, all calculations were performed using the traditional EVM method. Managers use cost estimates to complete (CEAC) to re-estimate the total cost of completing a project, which helps stakeholders more accurately assess the impact of changes in input data. This study used all three post-completion assessment approaches (PMI, 2017, Sixth Edition):

1) The first formula:

$$CEAC\ (\$) = AC + (BAC - EV) \qquad (1)$$

The above Equation indicates that the current deviation in the future will differ from the original estimate, i.e. It is the summation of the actual cost with the remaining cost of the work that needs to be completed.

2) The second formula has two different wordings, but the meaning will differ:

3) $$CEAC\ (\$) = AC + \frac{(BAC - EV)}{(CPI)} \qquad (2)$$

4) $$CEAC\ (\$) = \frac{BAC}{CPI}$$

Equation (3) is applied when the initial estimate is completed without deviation, which means the project progresses well at all levels. It can be assumed that CPI and SPI are maintained at appropriate levels. In such cases, managers should maintain ratios equal to one or greater than one.

3) The third Formula:

$$CEAC\ (\$) = AC + \frac{(BAC - EV)}{(CPI \times SPI)} \qquad (3)$$

Formula (3) is used to calculate the actual budget for the current day, with the remaining amount being adjusted based on performance, i.e. this formula is implemented when the current liquidity ratio corresponds to the initially predicted one.

Programming software and ML algorithms used

The programming language used to make predictions using ML models was Python.

Two ML algorithms, such as XGBoost and Random Forest, were chosen as the basis for subsequent analysis. One of the most famous and widely used models is the eXtreme Gradient Boosting (XGBoost) algorithm (Reddy, Teja, and Subhani, 2019).

It is necessary to divide the data into two subsamples to train the model: training and testing. It is also required to determine the input and source variables and implement the correct formula in the code. The total database of 110 projects was divided into three stages to see which stage would give us the best results, and which of the tools would be more suitable for early, middle and final predictions:

− Early stage: 1-29%;
− Middle stage: 30-69%;
− Late stage: 70-100%;

This approach which divides the projects according to stages and ranges was used earlier by Narbaev and De Marco (2014) in their article. This split approach is considered convenient for cost control, as the budget at the beginning of the project may be very different from what will be at the end.

Normalized EVM data (AC, BAC, EV, CPI, and SPI, depending on the formula used) were used from a database of already separated stages extracted from an MS Excel file and denoted as "x". The variable "y" was equal to the EAC value calculated using the traditional index formula. Next, for each file, the data was divided into a training set - 75% and a test set - 25% of the total data. The variables were implemented and trained through all three algorithms, separately, which were run through their libraries and hyperparameters. Then, as each algorithm predicted an outcome, it was compared to the EAC data calculated by the traditional method, and the percentage error (PE) and mean absolute percentage error (MAPE) were determined.

The percentage error (PE) is equal to the deviation between the cost estimate to complete (CEAC) and the actual cost to end (CAC) divided by the CAC multiplied by 100%. The percentage error indicates how significant the difference is between the cost of completion and the actual cost of projects. This indicator shows the accuracy of projects. Formula (4):

$$PE, \% = \frac{(CEAC - CAC)}{CAC} \times 100 \qquad (4)$$

Mean absolute percentage error (MAPE) shows a measure of relative error. It can be calculated using the previously calculated PE, specifically by summing all the resulting PE data for each project and obtaining the average for the data set. This indicator is expressed as a percentage and shows the accuracy and how much the model can be wrong in percentage terms. For example, if the metric showed that MAPE = 10%, the model error was 10% of the actual value.

Formula (5):

$$MAPE, \% = \frac{1}{n}\sum_{i=1}^{n} |PE_i| \qquad (5)$$

PE – error percentage for each project;
n – number of projects.

The higher the score, the greater the variability in the range, indicating higher risk; the lower the indicator, the more the values are clustered around the average and indicate low volatility.

First, overall trade data is presented, followed by a discussion of the most significant changes in 2022. As most of the changes were related to Kazakhstan's export structure, a comparison of these changes with Russian imports and the list of sanctions is provided.

4. FINDINGS AND DISCUSSION

This section examines the obtained values using the traditional EVM index method, which was separately calculated in an MS Excel spreadsheet using 3 EAC ($) equations and two ML algorithms. As noted earlier, the database was divided into three phases for more accurate forecasting since there was a different amount of work done at the beginning and end of the project, which also affected the budget spent during this time. Below is what the database looks like for an early stage, and the other files follow the same sequence. The early-stage dataset is given in Figure 1.

Project	Tracking _period	AC	BAC	EV	CPI	SPI	BAC.1	EV.1	AC.1	CAC	const_
1	1.1	13526.64	180485.27	13526.64	1,000	1,000	1,000	0.075	0.075	1,000	1.039
2	2.7	23426.56	180759.44	22454.88	0.959	0.52	1,000	0.124	0.13	1.057	1.039
3	3.4	49234.67	484398.413	48729.174	0.99	0.971	1,000	0.101	0.102	1.022	1.039
4	4.2	283418.65	3027133.186	253804.57	0.896	0.326	1,000	0.084	0.094	1.025	1.039
5	5.46	269856.492	21369835.51	263752.622	0.977	0.728	1,000	0.012	0.013	1.220	1.039
...	...	...	...	...	...	...	...	...	...	...	...
106	106.6	386654.38	4318950,0	470150,0	1.216	1.242	1,000	0.109	0.09	0.98	1.039
107	107.2	424560.24	1456000,0	418322.173	0.985	0.799	1,000	0.287	0.292	1.014	1.039
108	108.3	119086.966	1512000,0	118037.415	0.991	0.804	1,000	0.078	0.079	1.015	1.039
109	109.2	4000,0	107500,0	1400,0	0.35	0.118	1,000	0.013	0.037	1.087	1.039
110	110.1	6050,0	114700,0	5700,0	0.942	0.513	1,000	0.05	0.053	1.118	1.039

FIGURE 1. Early-Stage Dataset

Note: compiled by authors

Each of the algorithms applies normalized data to the BAC. Equation (1) uses the variables BAC, EV and AC as inputs for “x”. Equation (2) uses the variables BAC, EV, AC and CPI, and Equation (3) uses the variables BAC, EV, AC, CPI and SPI. EAC is used for the dependent variable “y” which was calculated using the traditional index method. Algorithms that work with regression to predict machine learning and work based on train-test validation were selected. The test and training data are divided into 25% and 75% randomly selected projects based on the number of projects used, respectively. All data is first trained on 75% of the data, and then the remaining 25% is trained and predicted. Since the algorithm takes any 25% of the projects from the embedded database into the code, to determine the fixed MAPE range by applying algorithms to compare with the selected MAPE index method, 100 MAPE trials were obtained. The code was run five times, i.e. the study used 500 random estimates to determine the exact MAPE range. One of the distinctive aspects of implementing algorithm codes in their model is the use of hyperparameters, which help to properly tune the tool and prevent it from overfitting, leading to better results. The following will clearly show how hyperparameters raise the performance of the model. Therefore, it’s important to know which of them critically impacts on project cost. Next, we'll show how hyperparameters improve model performance.

Index method results

MS Excel was used to analyze and calculate the index method, and EAC ($) values were calculated using three equations. Table 1 shows that the values of all three index calculations differ, confirming their purpose.

TABLE 1. MAPE result for traditional EVM method

MAPE results	Index-1	Index -2	Index -3
Stages/Equations	*CEAC = AC + (BAC - EV)*	*CEAC = AC + [(BAC - EV)/CPI]*	*CEAC = AC + [(BAC - EV)/CPI×SPI]*
Early	12.45%	14.11%	38.59%
Average	8.32%	7.21%	13.45%
Late	2.29%	2.36%	2.51%
Note: compiled by authors			

For example, we discuss Equation (1), which shows the best results. Still, this Equation only considers the project's current cost, summing it up with the remaining cost of the work until completion. Equation (2) is calculated based on past costs, and Equation (3) considers the cost and schedule of the project. Therefore, given the focus of this study on cost forecasting, the most accurate of the three EAC ($) is Index-2 (Equation 2).

Results of ML algorithms

XGBoost algorithm results

The Python programming language was used for forecasting through the XGBoost (XGB) tool. The algorithm learns from previous mistakes, making it theoretically one of the most reliable among thousands of machine learning algorithms. Table 2 shows the resulting MAPE data using the XGB algorithm without applying the tuned hyperparameters.

TABLE 2. MAPE results for the XGBoost model without hyperparameter tuning

Equations	XGBoost - Index-1	XGBoost - Index -2	XGBoost - Index -3	Note
Stages	Input data: BAC, AC, EV	Input data: BAC, AC, EV, CPI	Input data: BAC, AC, EV, CPI, SPI	
Early	3.51-4.05	14.51-16.22	80.79-133.29	99 projects (average actual cost overrun - 1.0392 (3.92%))
Average	6.89-7.56	13.21-14.84	24.1-25.15	107 projects (average actual cost overrun - 1.037 (3.70%))
Late	12.36-13.56	12.45-13.59	11.88-14.25	110 projects (average actual cost overrun - 1.032 (3.20%))
Note: compiled by authors				

As seen in Table 2, each algorithm has its unique hyperparameters. In this analysis, was used the reg_alpha parameter because it allows the algorithm to penalize the tree (i.e., the data) if it exceeds a specific value in the code, making the prediction line smoother. The algorithm learns from previous errors, that is, by looking at previous predicted data, which makes it theoretically one of the most reliable among thousands of ML algorithms (see Table 3).

Each stage has its reg_alpha value because each stage has different projects. For example, early has 99 projects, middle has 107, and late has 110 projects. Each stage uses different amounts of data because the data has been divided according to the scope of work. The “training test suites and evaluation criteria” portion included a percentage of the volume, which prevented the inclusion of data that would have been in the early or mid-stages. To summarize, the algorithm's prediction becomes better and more accurate when using parameters.

TABLE 3. MAPE results with the XGB reg_alpha hyperparameter

Stages	XGB - Index-2	Notes on the parameters used
Early	6.46-9.26	reg_alpha=7 for 99 projects
Average	6.47-8.67	reg_alpha=6 for 107 projects
Late	6.22-8.32	reg_alpha=5 for 110 projects
Note: compiled by authors		

Results of the Random Forest Algorithm

This algorithm is also considered part of a consensus algorithm built from several trees. The model implemented in this algorithm also used a test and train data method, randomly taking each row for prediction. Without adjustable hyperparameters, the model produced the results shown in Table 4.

TABLE 4. MAPE results for the Random Forest model without hyperparameter tuning

Equations	RF - Index -1	RF - Index -2	RF - Index -3	Note
Stages	Input data: BAC, AC, EV	Input data: BAC, AC, EV, CPI	Input data: BAC, AC, EV, CPI, SPI	-
Early	3.26-3.78	14.82-16.08	78.30-84.15	99 projects (average actual cost overrun - 1.0392 (3.92%))
Average	6.41-6.28	12.96-14.17	22.49-23.11	107 projects (average actual cost overrun - 1.037 (3.70%))
Late	6.91-7.42	11.99-13.42	12.25-12.95	110 projects (average actual cost overrun - 1.032 (3.20%))
Note: compiled by authors				

Table 4 shows that the RF model has a more accurate MAPE than XGB, which means it performs better on small data sets. Unfortunately, RF does not have parameters that penalize like XGBoost, so we used another way to improve the prediction, such as parameters max_depth = 3;4;5 (sequentially across stacks) and n_estimators = 90. The hyperparameter max_depth is used to determine the depth of each decision tree, and n_estimators show how many generalized trees should be in the forest. Different values of both hyperparameters were tested, but only the above values showed little improvement over data without hyperparameters. Typically, these options are best for increasing and improving results, but this didn't impact performance in the analysis. The obtained data is shown by Equation (2) - Index-2.

The values changed by a maximum of 1.5%, as shown in Table 5.

TABLE 5. MAPE results with hyperparameters for RF

Stage	RF - Index-2	Notes on the parameters used
Early	13.44-14.51	max_depth=3; n_estimators=90 for 99 projects
Average	12.51-13.89	max_depth=3; n_estimators=90 for 107 projects
Late	11.84-12.92	max_depth=3; n_estimators=90 for 110 projects
Note: compiled by the authors		

However, any model can allow the data to be double-checked so the parameters are adjusted. The following patterns can be derived for MAPE by summing the results for all used algorithms. All machine learning algorithms (without tuning) are better at predicting Index-1 (Equation 1) and the formula for the early and middle sections than the traditional index method in contrast to the late stage, at which the index method predicted better; for Index-3 (Equation 3), the traditional method predicted better than the other methods (without adjustment). In the Index-2 formula (Equation 2), the performance for the early stage of the RF algorithm was better than in other models, including those based on the index method. All indicators are calculated without setting hyperparameters. However, the traditional index method predicted better in the middle stage than all algorithms without hyperparameter tuning. These comparisons may not be accurate because some parameters severely overtrain the model with errors, so the results were compared to the setting. XGB with hyperparameter tuning is the most accurate project cost predictor for all three CEAC ($) formulas used early and mid-stages. PE was calculated for each project separately, showing the deviation between the total actual value and the predicted value (EAC ($)).

The main findings of the study are as follows:

– MAPE results for XGBoost with hyperparameter tuning showed the most accurate values for all three calculations for the early and middle stages.

– When tuning hyperparameters, MAPE values were changed only in XGBoost, although in practice, RF works more with small data sets. The results also show that some of the fastest and most accurate algorithms in practice will most likely not be able to work with small databases since the tool was initially designed to process large and complex data in a matter of seconds.

– Since it was clear that XGBoost was the most accurate in predicting the value, it was compared with the index method in Equation (2) when comparing other evaluation criteria to ensure that it was expected well. Analysis of the accuracy and frequency determination among the methods confirmed the above prediction, concluding that the model using the XGB algorithm produces the best predictions.

5. CONCLUSIONS

The paper concludes highlighting two contributions to the field of project management. First, the analysis found that the ML algorithm predicts more accurately and faster than the classical EVM method. Second, although all three selected algorithms showed their high performance and applicability for cost prediction, it was found that the model with the implementation of the XGBoost algorithm showed the most accurate results. In addition, the algorithm predicts the data in a matter of seconds. Thus, the above algorithms can be used by various project-oriented organizations and enterprises implementing projects and programs in multiple fields to predict costs and budgets.

The research limitations are that only 110 projects, a small database for the algorithms, were included in this work. In addition, there is no classification of projects according to specific fields that may allow us to compare the algorithm's impact on project cost. That's why several recommendations for future research have been identified. First, expanding the database. Feeding as much data into the model as possible can help improve data forecasting, as many tools are more geared toward big data. Second, it is recommended to study to test other algorithms or types of analysis. For example, future researchers may develop a more accurate model for cost forecasting or conduct new analysis using different algorithms, such as neural network algorithms or other algorithms operating on trees. Third, they can take cluster analysis as a basis, or rather, conduct analysis only in one area (banking system, construction, etc.), since in this work, the analysis was carried out using projects of all types presented in the study database.

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