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APPLICATIONS OF NON-TRADITIONAL EARNED VALUE MANAGEMENT MODELS IN PROJECT ANALYTICS

Abstract

Effective management of financial resources in projects is crucial for project success. Often, difficulties with financial resources, such as budget overruns, lead to unfavorable consequences that directly impact the successful completion of the project, the quality of the outcome, and stakeholder satisfaction. Therefore, identifying and developing tools for the effective management of financial resources, is of paramount importance. The purpose of this study is to apply non-traditional earned value management (EVM) models based on machine learning to predict project costs. To achieve the research objectives, previous literature on the topic was analyzed, a dataset of past projects was prepared, and a machine learning model was applied. The study found that non-traditional models, such as the regression algorithm AdaBoost, produced results close to the actual costs. The research indicates that the developed model could become an indispensable tool for project management and business decision-making, as it demonstrates the ability to adapt to various conditions and make accurate forecasts.

Key words: Project management; Artificial intelligence; Machine learning; Earned Value Management; Cost forecasting.

Introduction

In recent years, artificial intelligence has become an important tool in many aspects of human life, having a significant impact on the final results of human activity, including in such activities as project management. The study of this influence is becoming increasingly relevant in the context of growing digitalization and competition in the global market.

Numerous studies have been devoted to various aspects of the use of artificial intelligence in medicine, the military, industry, and the entertainment industry, but the issue of the use of artificial intelligence in project management remains poorly understood.

The main problem is the lack of knowledge about how various machine learning algorithms in project management can be applied and influence the outcome of forecasting various aspects of project management.

For instance, using machine learning for project cost forecasting is a promising application, although research on this topic is minimal [1]. The appeal of this topic lies in the need for new, alternative tools to perform such tasks, as the traditional EVM method is not always accurate and can be time-consuming.

This study aims to compare the traditional method of project cost forecasting with a non-traditional model using an algorithm such as AdaBoost. The following tasks will be addressed to achieve this goal: data collection, machine learning model building and testing, and comparative analysis.

The scientific novelty of the research lies in the identification of accurate algorithms for machine learning in order to predict Estimate at Completion (EAC) of a project, which can have the greatest impact on the development of artificial intelligence in project management. The practical significance of the work consists of developing recommendations for project managers involved in project management ways to optimize and forecast accuracy in project management.

Literature Review

According to the research paper "The Application of Artificial Intelligence in Project Management Research: A Review" by Gil et al. (2021), there are three stages of implementation, from the integration of automation and software to the application of artificial intelligence in project management. Task automation programs like Microsoft Project and Primavera (Oracle), which debuted in 1983, were integrated during the first phase. Chatbot assistants have been utilized in management equipment recaps and reminders for meetings in recent years. Although chatbots have become a part of our daily lives, project management is still a relatively new field for them. The most basic artificial intelligence notion marked the start of the third level. Machine learning has been utilized in project management to facilitate predictive and corrective analysis [2]. This is done to give the project manager information to make decisions about, for instance, how to plan and manage project resources within specific parameters and restrictions or how to handle issues and risks based on past project success. Within less than a decade, artificial intelligence (AI) is anticipated to utilize historical project lessons to propose new project schedules that are dynamic and capable of real-time adjustments based on resource performance and project progress.

Artificial intelligence (AI) programs are capable of analyzing data to identify trends and provide choices that align with those patterns [3]. Trending in software development projects and organization management, they are structured and coded to learn from the data they have access to through programming techniques, either naturally occurring at the time of their style or continuously to improve computer systems' performance through information exposure without the need to follow explicitly programmed directions of AI. The following are trends in organization management and software development projects: Machine Learning (ML), Deep Learning (DL), Speech Recognition (SR), and Natural Language Processing (NLP) [4].

Artificial intelligence may aid project managers with repetitive tasks, including creating project plans, entering and managing data, and more. These are jobs that can be completed automatically. When AI takes care of the majority of the administrative tasks, project managers have more time and energy to focus on the actual work. AI is capable of estimation, recommendation, and optimization. AI is able to learn from and infer future project development scenarios based on historical project management data. Apart from automation, one of the main applications of AI in project management is the collection and organization of data from many sources to generate informative project assessments. The links that AI can identify in data would be invisible to even the most trained human eye. AI is helpful for complex analysis as well. It can obtain far more information than a manager who is limited to human knowledge. When AI is employed, for example, value and risk assessments can be completed by human operators more rapidly and with less effort. Artificial intelligence is able to solve a number of project management issues, including risk assessment and management, resource management, cost management, and time management [5].

The application of artificial intelligence for predicting key project aspects, such as cost or duration, is a novel but highly relevant field in project management.

Despite the growing popularity of machine learning (ML) and AI applications in various aspects of human life, interest in some areas is only beginning to emerge. Specifically, in project cost estimation within project management, only a few studies have been conducted on the effectiveness of the practical application of machine learning and AI. The scarcity of literature in this field, according to Inan et al. (2022), is linked to the fact that each project is unique, and predicting project outcomes using limited historical data is ineffective.

The noted scarcity of literature in this field does not imply the absence of relevant works. There are studies where machine learning, particularly algorithmic models, has been applied to predict project cost or duration.

For example, Elmousalami (2020) investigated 20 AI techniques, such as fuzzy logic, artificial neural networks, regression analysis, hybrid models like the genetic fuzzy model, and ensemble methods (XGBoost) and random forest, to create a model for predicting project costs based on comparisons. As a result of the research that was conducted, emphasizing the importance of ensemble methods, the author concluded that XGBoost is the most accurate and reliable model.

Additionally, it was observed that ensemble method algorithms demonstrate high performance and relatively high accuracy in this study.

In another study conducted by Balali, A. et al. (2020), the researchers aimed to improve the effectiveness of the Earned Value Management (EVM) method by employing Artificial Neural Networks. In this investigation, the authors utilized two distinct machine learning models, namely Artificial Neural Network (ANN) and multiple regression analysis, to enhance the accuracy of cost forecasting based on data from 50 road construction projects in Iran. The findings indicated that both Artificial Neural Network (ANN) and multiple regression analysis outperformed the traditional EVM method in terms of precision. When comparing the performance of the two models using metrics such as Mean Squared Error (MSE) and an R2 value, the authors concluded that Artificial Neural Network (ANN) was the superior model.

Narbaev et al. (2023) utilized real cost data from 110 projects to compare the forecasting performance of the XGBoost model against traditional index-based methods, as well as other machine learning algorithms (SVM, CatBoost, RF, LightGBM), and two non-linear growth models (Gompertz and Logistic). Based on the results of the comparative analysis, the XGBoost model was selected by the authors due to its superior accuracy, low error rates, and ability to handle various types of data efficiently. To evaluate the model results, the authors employed three criteria: MAPE (accuracy), NRMSE (timeliness), and prediction performance (frequency). Consequently, the authors concluded that based on all three evaluation criteria, the XGBoost model exhibited the most precise results, thus proving its reliability.

Additionally, Ottaviani and De Marco (2022) developed a multiple linear regression model based on three regressors: EAC, CPI, and WP. The model was tested on 29 real projects and compared with the traditional index-based Earned Value Management (EVM) method. As a result, the authors concluded that the new model for EAC estimates demonstrated improvements in accuracy and lower variance compared to the traditional method.

In conclusion, based on the review of previous literature, it was determined that machine learning, when sufficiently trained with adequate data, can predict the cost or duration of a project more accurately than traditional methods.

Materials and methods

Analytical methods.

A systematic approach is required for conducting research in any field of science. This approach includes aspects such as detailed research planning, selection of appropriate analysis methods, definition of research questions or hypotheses, and testing of those hypotheses.

The research methodology can provide such a structured approach. The historical development of research processes has led to the classification of research into three categories: quantitative research, qualitative research, and mixed-method research [10].

The mixed-method approach used in this study, combines quantitative and qualitative research methodologies. Although this approach requires more time and skills, studying the same question using different methods and sources helps to better explore various aspects of the subject area from different perspectives.

The quantitative approach revolves around working with numerical data. This approach is used for deductive or statistical analysis, where it is necessary to test or confirm a particular theory or hypothesis. The methods for collecting numerical data in this approach can take the form of surveys, observations, or experiments. Compared to the previous method, research in the qualitative approach is based on philosophical assumptions [10]. This method describes concepts, experiences, and viewpoints without relying on numerical values.

In this work, a literature review of the subject area was conducted as part of the qualitative research approach. Relevant articles were searched through online databases such as Scopus, Google Scholar, and ResearchGate. As a result, a literature review grid consisting of 30 relevant articles was created. Subsequently, based on previous works on machine learning, an appropriate machine learning algorithm was selected. When selecting an algorithm for analysis, attention was paid to the type of task, in our case, predicting numerical values, as well as to accuracy and robustness. As part of the quantitative research approach, a dataset was created based on data from the Operations Research & Scheduling research group [11] website. The data obtained from this website is based on actual projects completed by various industries.

Earned Value Management (EVM). Cost forecasting.

To predict the cost, the calculations use data on the planned value, earned value, actual costs, planned duration, actual duration, budget at the time of completion, performance index from schedule, and cost performance index. A cost estimate at completion was calculated using a number of different formulas. The top three formulas that are used are [12]:

$$\text{a) } CEAC(\$) = \frac{BAC}{CPI} \tag{1}$$

This formula a) is used when the project is moving forward without any obstacles, this calculation is the most recommended. Divide the BAC by the Cost Performance Index (CPI) to determine the EAC.

$$\text{b) } CEAC(\$) = AC + \frac{(BAC - EV)}{CPI * SPI} \tag{2}$$

As for formula b), it is used when costs increase and schedules are delayed, this formula is applied. In this instance, the Earned Value (EV) and the Schedule Performance Index (SPI) must be included in the calculation.

$$\text{c) } CEAC(\$) = AC + (BAC - EV) \tag{3}$$

In project management, when unforeseen circumstances have been eliminated and it is expected that interference in the operating mode will not occur until the completion of the project, this c) formula is applied.

The latter formula is used when a project experiences schedule delays, but it is expected that no further delays will occur until the project is completed. This may mean that the project is currently behind schedule, but it is assumed that it will continue to move forward without further obstacles or delays.

The Machine Learning algorithm used.

To predict continuous CEAC, we chose the Adaptive Boosting (AdaBoost) algorithm. Although this algorithm is not widely used for cost forecasting, its effectiveness in prediction has been noted in many other professional fields. Additionally, beyond this advantage, the algorithm is easy to implement and performs well with small datasets, which also influenced our decision when selecting algorithm for analysis.

The Adaptive Boosting algorithm is a popular and effective method in ensemble learning. It belongs to the family of boosting methods and works by combining weak learners, often decision trees. During the training process, the algorithm focuses on data points that were misclassified in previous iterations [13]. Each predictor in the model learns from the residuals of the previous predictor before being added to the model. This process continues until either the user-specified number of predictors is reached or an ideal predictor is found. With each iteration, the model improves. To make predictions, AdaBoost combines the trained predictors to create a strong model that produces more accurate results. The algorithm evaluates the output of each predictor, essentially weighting them through a voting mechanism [14], with the final prediction being the value that receives the most votes.

Evaluation metrics.

The train-test split is a widely used technique for evaluating a machine learning model. In this approach, the dataset meant for training the algorithm is split into a training set and a test set in a certain percentage ratio. The purpose of this technique is to assess how a model trained on training data will perform with new and previously unseen data. This helps to measure the accuracy and reliability of the model.

In this work, the prepared datasets were divided into two parts using the train-test split technique in a percentage ratio of 75% for training and 25% for testing the trained model.

Before starting the training and testing of the model, it was necessary to prepare the data, which involved preparing the dataset consisting of projects completed from 1% to 29% and determining all the features to be used as independent and dependent variables.

The project lifecycle is typically divided into three stages: early, middle, and late. We have determined the percentage intervals for each stage based on a review of relevant literature. For example, Narbaev et al. (2023) defined the interval for the early stage as 1–29%, for the middle stage as 30–69%, and for the late stage as 70–95%. We have used this approach in our work and have compiled a dataset for early stage with 1–29% completion. The reason for dividing a project into three stages is that the amount of work completed and the amount of money spent may differ at different stages of the project. So, comparing the project progress without dividing it into stages can be incorrect.

As a result of using this approach, a dataset consisting of 78 construction projects was formed.

The following features, such as BAC, EV, AC, PV, CPI, and SPI, were used as independent variables during model building to forecast the CEAC using formulas (1), (2), and (3), with EAC as the dependent variable.

Since the results obtained from the machine learning model on their own represent nothing without comparative analysis and evaluation, we used the RMSE metric to assess the quality, accuracy, and to obtain information about the model's performance. This metric calculates the difference between the actual cost and the predicted cost, as defined by Equation (4).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(CAC_i - EAC_i)^2} \tag{4}$$

where i is the given project, n is the number of projects, EAC is the predicted value and CAC is actual value (best value = 0; worst value = +∞).

Results and Discussion

During the training of the machine learning models, the training process was repeated a hundred times to compare the results of a hundred trials with just one. To obtain the results of a hundred trials, the outcome of each attempt, ranging from one to one hundred, was recorded in a special list. Then, to compare these with the results of a single trial, the average value of a hundred trials was calculated. The results of comparing the two methods are presented below.

Moreover, all the provided results of the models were obtained based on hyperparameter tuning. Choosing parameters for the algorithm instead of using default values shows better trainability and improved results. Since chosen algorithm have its own set of hyperparameters, which differ from each other in quantity and performed functions, it was necessary to automate the process of parameter selection. For this purpose, we used the GridSearchCV function, which selects the best combination from the specified parameters.

Traditional index-based method results.

When calculating the results for the traditional index-based EVM method, formulas CEAC (1), (2), and (3) were utilized. All calculations based on these mentioned formulas were performed in Google Sheets tool. The results of RMSE for the traditional method which are presented in Table 1, were obtained using the scikit-learn library in the Jupyter Notebook environment.

Table 1 – The results of RMSE for the traditional method*

Indexes / Stage	Index-1 (CEAC-1)	Index-2 (CEAC-2)	Index-3 (CEAC-3)
Early	0.024	0.265	1.438

*Source: Conducted by the authors.

Based on the obtained results, it can be noticed that the performance of Index-1 is significantly better compared to Index-2 and Index-3. It is quite likely that the reason for this is its simplicity and direct calculation method because it directly adds the budget at completion (BAC) to the earned value (EV) without any additional adjustments based on cost performance or schedule performance indices. This means that the formula only considers the current project cost.

Among the three formulas, Index-2 is the most suitable for predicting the future project cost because it takes into account past cost performance indicators. In Table 1, the results for Index-3 are significantly worse than the previous formulas because, in its calculation, both the cost performance index and the schedule performance index are considered.

Although Index-2 is better suited for further analysis, all three formulas will be included when describing the results of the machine learning model. However, Index-2 indicators will be used when comparing the best model with the traditional EVM method.

Results from the AdaBoost algorithm.

Creating a machine learning model based on the AdaBoost algorithm involved hyperparameter tuning. To fine-tune the performance of the model, we utilized the GridSearchCV function. This function helped us to determine the optimal values for hyperparameters such as “n_estimators” and “learning_rate”. The parameter “n_estimators” is essential in determining the number of weak learners to be included in the model, as it is part of ensemble learning. On the other hand, the “learning_rate” parameter determines the contribution of each predictor to the final prediction. For this particular model, we chose a decision tree as the weak learner.

In Table 2 the results for single trail prediction are provided. The obtained results for all three formulas differ not so significantly, indicating that the algorithm effectively identifies patterns in the data and demonstrates stability in predictions. It can be concluded that the algorithm produces lower errors, a better fit and more accurate results when using the CEAC-2 formula for forecasting.

Table 2 – Single trail results of the AdaBoost-based model*

Evaluation metric	Early stage		
	Index-1 (CEAC-1)	Index-2 (CEAC-2)	Index-3 (CEAC-3)
RMSE	0.011	0.023	0.026

*Source: Conducted by the authors.

During the hundred trial model training, a special "for" loop with a counter was implemented. Empty lists were used to record the results after each iteration for calculating the average value of each metric.

The findings from the hundred trials training are presented in Table 3. Upon comparing the results for each of the three formulas, significant differences can be observed. Similar to the single trial training, CEAC-2 produced the best results among the three formulas. Compared to CEAC-1 and CEAC-3 formulas, the second formula generated lower errors.

If we compare the results of single trial and hundred trials, we can notice that the performance metrics generally exhibit similar trends, with some differences in the exact values. For instance, the RMSE score for CEAC-1 formula is slightly higher in the hundred trials compared to the single trial. However, overall, the results for single trial are noticeably better.

Table 3 – Hundred trial results of the AdaBoost-based model*

	Early stage		
Evaluation metric	Index-1 (CEAC-1)	Index-2 (CEAC-2)	Index-3 (CEAC-3)
RMSE	0.018	0.072	0.083

*Source: Conducted by the authors.

Comparing the results, it can be observed that training the model one hundred or more times has a slight but negative impact on its accuracy. To identify the best method for project cost forecasting, we chose the model trained only once.

A comparative analysis of the results from the traditional method and the model trained once revealed that the accuracy of the machine learning algorithm exceeds that of the traditional method when applying all formulas.

Conclusion

This work aimed to utilize artificial intelligence, specifically machine learning, to predict the Budget at Completion (BAC) of projects. By applying this technology, we sought to determine the extent to which machine learning could be more accurate than the traditional index-based method. The study revealed that not only does the algorithmic machine learning model perform better at predicting project costs compared to the traditional method, but it also concluded that with the availability of large datasets for training, machine learning could become an indispensable tool for decision-making not only regarding project budgets but also other critical aspects of projects.

Overall, the work on this study consisted of several stages, including a literature review of the subject area, preparation of a dataset for training and testing the machine learning model, selection of the development environment, selection of appropriate machine learning algorithm, training and testing of the models, and analysis and comparison of the results obtained.

The dataset prepared for training the models was compiled based on real completed projects, which is a significant advantage of this work. Real data contains complex scenarios and exceptions, ensuring the model's relevance to project management and increasing its applicability to real-world projects. The dataset compiled for training and testing the models consists of a total of 117 projects. Based on this dataset, one subset consisting of 78 construction projects was created for the early stage.

For this study, an ensemble machine learning algorithm such as AdaBoost was selected. This algorithm was chosen for its accuracy and robustness, as it can be trained on small datasets while providing reliable and stable predictions. Since the target variable to be predicted is a continuous value, the following metric, which is designed to evaluate regression model performance, was chosen for the assessment and analysis of the results: RMSE.

When comparing algorithmic models to identify the best one, a comparative analysis of single-trial and one-hundred-trial training for the model was also conducted. This comparison aimed to understand the extent to which training more than once could improve or worsen the prediction results. Given the effectiveness of this approach, it is also important to mention that hyperparameter tuning was applied during model construction.

Overall, the comparison of results between the single-trial-trained model and the hundred-trial-trained model yielded relatively interesting results. For instance, training a hundred times showed a deterioration in results. The primary analysis, which compared the machine learning model with the traditional index-based method, concluded that the machine learning algorithm can generally predict project costs at an early stage much more accurately.

The main contribution of this work is in the proposed machine learning algorithm calculates the cost estimates under uncertainty and improves the EVM field. In conclusion, this study confirmed the hypothesis that machine learning outperforms the traditional method. Using this technology as a decision-making tool can alleviate the workload of the project team and project manager and improve project management processes.

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ЖОБАЛЫҚ ТАЛДАУДА ИГЕРІЛГЕН КӨЛЕМНІҢ ДӘСТҮРЛІ ЕМЕС МОДЕЛЬДЕРІН ҚОЛДАНУ

Аңдатпа

Қаржылық ресурстарды тиімді басқару – жобалардың сәтті орындалуы үшін шешуші фактор. Жобаның бюджеттен асып кетуі сияқты қаржылық ресурстарға байланысты қиындықтар көбінесе жобаның табысты аяқталуына, нәтижелердің сапасына және мүдделі тараптардың қанағаттануына тікелей әсер ететін жағымсыз салдарға әкелуі мүмкін. Сондықтан қаржылық ресурстарды тиімді басқару құралдарын іздеу және дамыту қазіргі уақытта өте өзекті мәселе болып отыр. Ғылыми жұмыстың мақсаты – жобалық шығындарды болжау үшін машиналық оқытуға негізделген игерілген көлемді басқарудың (EVM) дәстүрлі емес модельдерін қолдану. Бұл мақсатқа жету үшін зерттеуде осы саладағы алдыңғы тәжірибелер талданды, аяқталған жобалар бойынша деректер қоры жиналып, машиналық оқыту моделі қолданылды. Зерттеу нәтижелері AdaBoost регрессия алгоритмі сияқты дәстүрлі емес модельдердің дәстүрлі әдістермен салыстырғанда нақты шығындарға жақынырақ нәтижелер көрсететінін айқындады. Сонымен қатар, алынған мәліметтер әзірленген модельдің жобаларды басқару мен бизнес шешімдерін қабылдауда маңызды құралға айналуы мүмкін екенін дәлелдеді.

Тірек сөздер: Жобаны басқару, жасанды интеллект, машиналық оқыту, игерілген көлем әдісі, шығындарды жоспарлау.

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ПРИМЕНЕНИЕ НЕТРАДИЦОННЫХ МОДЕЛЕЙ МЕТОДА ОСВОЕННОГО ОБЪЕМА В ПРОЕКТНОЙ АНАЛИТИКЕ

Аннотация

Эффективное управление финансовыми ресурсами в проектах имеет решающее значение для их успешного выполнения. Часто проблемы с финансовыми ресурсами, такие как перерасход бюджета, приводят к неблагоприятным последствиям, которые непосредственно влияют на успешное завершение проекта, качество результата и удовлетворенность заинтересованных сторон. Поэтому идентификация и разработка инструментов для эффективного управления финансовыми ресурсами имеет первостепенное значение. Цель данного исследования – применить нетрадиционные модели управления освоенным объемом (EVM), основанные на машинном обучении, для прогнозирования затрат на проект. Для достижения целей исследования был проанализирован предыдущий опыт в данной области, подготовлен набор данных по прошлым проектам и применена модель машинного обучения. Исследование показало, что нетрадиционные модели, такие как алгоритм регрессии AdaBoost, продемонстрировали результаты, близкие к фактическим затратам. Результаты исследования свидетельствуют о том, что разработанная модель может стать незаменимым инструментом для управления проектами и принятия бизнес-решений, так как она демонстрирует способность адаптироваться к различным условиям и делать точные прогнозы.

Ключевые слова: управление проектом, искусственный интеллект, машинное обучение, метод освоенного объема, прогнозирование затрат.

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