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RESEARCH

Evaluating the impact of construction delays on project duration using machine learning and multi-criteria decision analysis

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Abstract
Construction projects are inherently complex and prone to delays, significantly impacting project timelines and costs. This study addresses the critical issue of construction delays in Jordan by leveraging advanced methodologies such as Gaussian Process Regression (GPR) and the Analytical Hierarchy Process (AHP). The problem of accurately predicting and managing delays in construction projects has long challenged the industry, with existing approaches often failing to account for the multifaceted nature of delay factors. This research integrates GPR, a machine learning technique, with AHP, a Multi-Criteria Decision Analysis (MCDA) tool, to evaluate and predict the impact of delay factors on project duration. The study employs a comprehensive dataset comprising 191 construction projects in Jordan, with critical variables identified through expert evaluations and literature reviews. The GPR model demonstrated superior predictive capabilities, achieving an R^2 value close to 1, indicating its high accuracy in forecasting time and cost overruns. The AHP model, on the other hand, prioritized weather conditions and unrealistic contract requirements as the most significant contributors to delays. The findings suggest that the combined application of GPR and AHP offers a robust framework for predicting and managing construction delays, providing valuable insights for improving project management practices. Future work should focus on expanding the dataset and refining the models to enhance their applicability across different regions and project types.

Keywords Construction delays · Construction management · Machine learning · Multi-criteria decision analysis · Jordan

Introduction

Construction projects are inherently complex, requiring careful planning, organization, and execution. However, delays are expected, leading to extended project durations and increased costs, which have global financial implications (Odeh & Battaineh, 2002; Flyvbjerg, 2014). Despite efforts to make the construction industry more predictable and regulated, many projects worldwide still fail to meet their deadlines (Sambasivan & Soon, 2007). The construction sector experiences higher delays and lower productivity rates than other industries (Alsharef et al., 2021). The challenge lies in the unpredictability and complexity of construction projects, making it difficult to accurately forecast delays and their impact (San Cristóbal et al., 2018).

Optimizing project duration forecasting in construction management, especially within the housing and planning sectors, is vital for reducing delays and avoiding cost overruns. The application of Artificial Intelligence (AI) and Machine Learning (ML) in civil engineering has opened new avenues for improving the accuracy and reliability of these forecasts (Kaveh, 2014; 2017; Kaveh & Eslamlou, 2020; Kaveh et al., 2016; Kaveh et al., 2020). By leveraging advanced AI and ML techniques, construction managers can analyze complex data sets to identify potential risks and inefficiencies that might go unnoticed with traditional methods. This data-driven approach enhances decision-making processes, ensuring housing and planning projects are completed within the expected time. The difficulty in predicting delays is compounded by the complex interplay of factors affecting construction projects. Various strategies from the

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manufacturing sector have been applied in construction with mixed results (Heigermoser et al., 2019).

Predicting delays remains challenging due to the inability to account for all interacting elements throughout a project's lifecycle (Pan & Zhang, 2021). The classification of delays into avoidable and unavoidable categories is crucial in delay analysis, though there is often debate over how specific causes should be categorized (Çevikbaş & Işık, 2021). Resource shortages, for instance, may be seen as unavoidable, but proactive measures can be taken to mitigate their impact through proper planning (Iqbal et al., 2021).

Due to the complexities above, estimating delay risks in construction is challenging in the real world. Professionals often rely on qualitative assessments of project progress indicators, which are difficult to translate into quantitative models for precise delay prediction (Kabirifar & Mojtahedi, 2019). The critical challenge is developing a practical model that quantifies these qualitative factors to accurately estimate the risk and severity of potential delays (Cooper et al., 2005).

Recent studies highlight the potential of Artificial Intelligence (AI) and Machine Learning (ML) in improving delay predictions and overall construction management (Kaveh, 2024; Shihadeh et al., 2024; almahameed & Bisharah, 2024; Arabiat et al., 2023). Gondia et al. (2020) found that machine learning models, specifically decision trees and naive Bayesian classifiers, could effectively predict the extent of project delays. These models validated through cross-validation testing, demonstrated superior prediction performance, particularly the naive Bayesian model, which enabled proactive risk management based on evidence (Iranmanesh & Kaveh, 1999).

Sanni-Anibire et al. (2021) also explored the use of machine learning for mitigating construction delays, identifying cost estimation, duration prediction, and delay risk assessment as critical applications. Industry experts considered and validated techniques such as Multi-Linear Regression Analysis, K-nearest neighbors, Artificial Neural Networks, and Support Vector Machines. The study developed and verified a framework for addressing construction delays, showcasing the potential of AI and ML in resolving industry challenges.

Furthermore, Sanni-Anibire et al. (2020) developed a dataset from 36 identified delay risk factors, applying ML techniques like K-Nearest Neighbors, Artificial Neural Networks, and Support Vector Machines to manage project risk in tall structures. The Gaussian Process Regression (GPR) model, a non-parametric and advanced regression technique, has also been highlighted for its capability to predict future events based on past data and generate uncertainty estimates (Rasmussen, 2003; Mahmoodzadeh et al., 2022; Prakash et al., 2018; Djeziri et al., 2021).

In addition to AI and ML, the Analytical Hierarchy Process (AHP) has gained popularity as a Multi-Criteria Decision-Making (MCDM) tool. It helps eliminate decision-making gaps by capturing potential outcomes across various evaluation criteria (Afolayan et al., 2020; Kalutara et al., 2021). In the Jordanian construction sector, AHP has been used to assess the value and impact of construction delays on project timelines.

Despite the growing interest in AI and ML applications in civil engineering and construction management, there is a lack of studies combining AHP and GPR to evaluate the impact of construction delays. This study aims to fill that gap by using GPR and AHP to assess construction delays, with a case study from Jordan providing practical insights. The study aims to provide a framework for predicting and managing delays, offering insights into their causes and implications for better project management. The findings will contribute to the literature by evaluating delay factors using AHP and quantifying the uncertainty of these factors with GPR.

Methodology

AHP approach

Decision-making often requires more than just implementing an idea; it demands a deep understanding of the issue. The Saaty AHP is a straightforward, mathematically based multi-criteria decision-making tool capable of addressing complex, multi-attribute problems. It assigns weights to evaluation criteria based on pairwise comparisons made by the decision-maker, synthesizing these into a final score where higher weights indicate greater importance (Saaty, 2004).

This study examines real construction projects to demonstrate the effects of delays using the AHP framework, marking the first application of AHP in Jordan's construction sector. Delay factors, drawn from the literature (Zidane & Andersen, 2018; Aladayleh Jameel et al., 2020; Bekr, 2018), were evaluated by experts. The study presents an AHP-based tool for assessing construction project delays, integrating safety and income loss considerations through a multi-attribute decision-making process. Spice Logic software facilitated the AHP analysis, providing an efficient methodology. Given the prevalence of construction delays in Jordan, experts were carefully selected based on their industry experience, academic background, and knowledge of engineering project management to ensure reliable results (See Table 1).

Table 1 Study delay factors

Criteria	Description
Errors in design and documentation	A change order is an expansion or reduction of the scope of work for a contract. It may cause an increase or decrease in the price of the contract and/or an earlier or later completion date. The vast majority of projects, and especially larger ones, include some degree of change orders.
Delayed progress payments	Delays in making payments to a construction client negatively impact that client's performance, which in turn negatively affects the timeframe for the project's completion.
Ineffective project planning and scheduling	Inadequate preparation suggests that a timeline to which all team members are expected to comply has not been created. This leads one to believe that the task will not be completed on time, leading to shoddy workmanship and an increased risk of burnout.
Poor site management by contractors	The construction industry employs millions of people worldwide. The vast majority of them are employed in jobs that require no special skills or training. It is important to ensure that the project Documents are adhered to and that contractors and subcontractors are given appropriate supervision.
Inadequate contractor experience/ building methods and approaches	Bidding for projects by inexperienced contractors puts pressure on the performance of construction and infrastructure projects. If evidence is available to help you choose the best contractors for your project, this may be prevented by making the right choice of contractors.
Sub-contractors practices	The success of a construction project depends on a large number of subcontractors meeting their commitments on time. Even a single break in the chain may result in enormous delays and financial losses for the prime contractor and subcontractors.
Unrealistic contract duration and requirements	It is anticipated that the client will make some mistakes unintentionally for a variety of reasons, including a lack of estimating experience on the part of concerned technical people. This is the primary difficulty with estimating; however, this is not always the case.
Weather conditions	The construction sector is one of the most susceptible to the effects of bad weather. Weather conditions negatively impact around 45% of all building projects. These occurrences can influence project stakeholders, including slippage and reduced worker safety.

Gaussian process regression model

In this study, Gaussian Process Regression (GPR) is employed as a key methodology for evaluating the impact of construction delays on project duration. GPR, a probabilistic model, defines a distribution over functions f f: X → $\mathbb{R}$, where the values of f at any set of points $\{x_i\}_{i=1}^{N} \in X$ follow a multivariate Gaussian distribution (Rasmussen, 2003; Hoang et al., 2016; Hong et al., 2014). The model begins by defining a mean function $m(x)$ and a covariance function k (x, x′), which characterize the Gaussian process. These functions are specified by a set of hyperparameters that are inferred by minimizing the marginal likelihood (Li & Chen, 2018).

One of GPR's strengths is its ability to handle nonlinear data through the application of kernel functions. The process is fully defined by the mean and covariance functions, with the squared exponential covariance function often used for function approximation (Stahl, 2006; Pal & Deswal, 2010). The GPR model assumes that the output y is computed as $y = f(x) + \varepsilon$, where ε represents homoscedastic noise (Rasmussen, 2003).

In this study, Python was used to implement the GPR model, with the dataset divided into a training set (80%) and a test set (20%). To ensure robust model evaluation, a 5-fold cross-validation procedure was applied, minimizing the influence of randomness and allowing for accurate assessment of model performance (Berrar, 2019). The results showed that GPR provided the best forecasts across all performance evaluation criteria.

Data description

The methodology that was used in this investigation was a study of historical data. In addition, the use of historical data is beneficial in demonstrating a link between the key factors that influence the time, cost, and Overruns parameters of engineering projects, which is necessary for developing projections for the next projects (Asiedu & Adaku, 2019; Faten Albtoush et al., 2021; Gharaibeh et al., 2020). As a consequence of this, historical data on engineering projects (such as buildings, roads, tunnels, stadium repair, and so on) completed in Jordan between the years 2005 and 2021 have been collected from the Amman Municipality, the Ministry of Construction and Housing, and private companies and engineering offices. Every engineering project had its own unique set of sex variables, all of which were meticulously selected and thoroughly defined. The dependent variables and the independent variables are the two categories that fall under this category of explanatory factors.

- **Dependent Variables**

Based on the given data, the dependent variables are the Time overruns (%) and Cost overruns (%), with each project employed as the fundamental unit of observation.

- **Independent Variables**

After the dependent variables predicted by the GPR model had been identified, the essential next step was to generate

Table 2 Relative priorities (%) values for each main criterion

Criterion	Weight
Errors in design and contract documents/Change Orders	3.38
The client is not making the progress payments on time	6.59
Poor and Ineffective construction project planning and scheduling	11.73
Poor site management by contractors	11.89
Inadequate contractor experience/building methods and approaches	6.22
Sub-contractors practices factors	12.12
Unrealistic contract duration and requirements imposed	20.35
Weather conditions	27.73

independent variables that would explain variations in the amount of time and money spent on engineering projects.

These variables are based on parameters including:

- Parameter l: AC, Actual Cost.
- Parameter 2: PV, Planning Value.
- Parameter 3: AD, Actual Duration.
- Parameter 4: PD, Planning Duration.

Results and discussion

AHP model implementation

The numeric number that they used for this weight may range anywhere from 1 to 9. As a result of the larger number, it is reasonable to believe that the component has a greater amount of significance. Those who participated in the survey were given instructions on how to use the 1–5 scale right at the beginning of the exercise. The results of the pairwise comparison tables found in the questionnaire were averaged to provide comparison tables for each of the criteria and sub-criteria used in the decision model.

In order to evaluate the impact of construction delays on the overall length of the project from an expert's point of view. Following the completion of the first step, which consisted of determining the relative importance of each criterion in comparison to the others, the second step consisted of determining the amount of time that would be required to meet each criterion, and the third and final step consisted of selecting the precise amount of time that would be required to meet the overall criteria. At this point, the check that has been calculated is shown (If the CR value is smaller than 0.1). The results demonstrated, as can be seen in Table 2; Fig. 1, that the following primary findings were obtained:

- The (Weather conditions) criteria were assigned the greatest importance, and it received a percentage of 27.73%.
- The (Unrealistic contract term and criteria imposed) criterion came in at number two with a percentage of 20.35%, placing it in second place.
- Based on the importance placed on the criteria, the third priority, which was titled "Sub-contractors' Practices Factors," was awarded 12.12% of the total ranking.
- With a percentage of 11.89% and 11.73%, the (Poor et al. by Contractors and Poor Site Management by Contractors) respectively criteria are ranked fourth.
- With a percentage of 6.59% and 6.22%, the (The client is not making the progress payments on time and Inadequate contractor experience/building methods and approaches) respectively criteria are ranked fifth.
- With a proportion of 3.38%, the (Errors in design and contract documents/Change Orders) criteria are the least important.
- It is worth mentioning that the CR ratio 0.068 for these main criteria which <0.1 is OK.
- Regarding Relative Priorities (%), for instance, the Errors in design and contract documents/Change Orders criteria:
- Relative Priorities (%) = Priorities $\times$ 100% = $0.0334 \times 100\% = 3.38$.

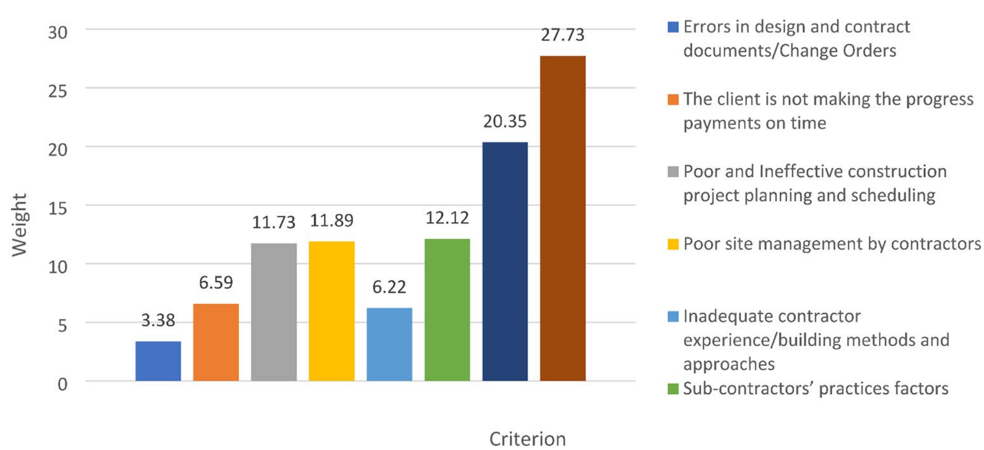

Fig. 1 Relative priorities (%) chart for the study's main criteria

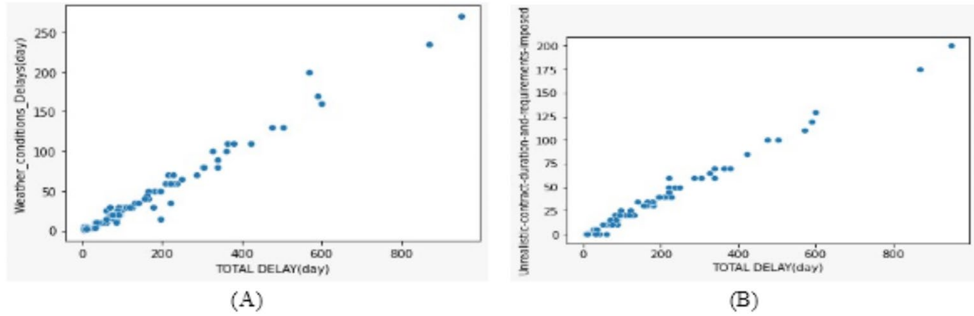

Fig. 2 Displaying the connections between the variables in the input using scatter plots. (in days) “Total Delay” and “Weather Conditions Delay” (A) Correlation between “Total Delay” and “Unrealistic Contract Duration and Requirements Imposed” (B) Correlation between. (in days)

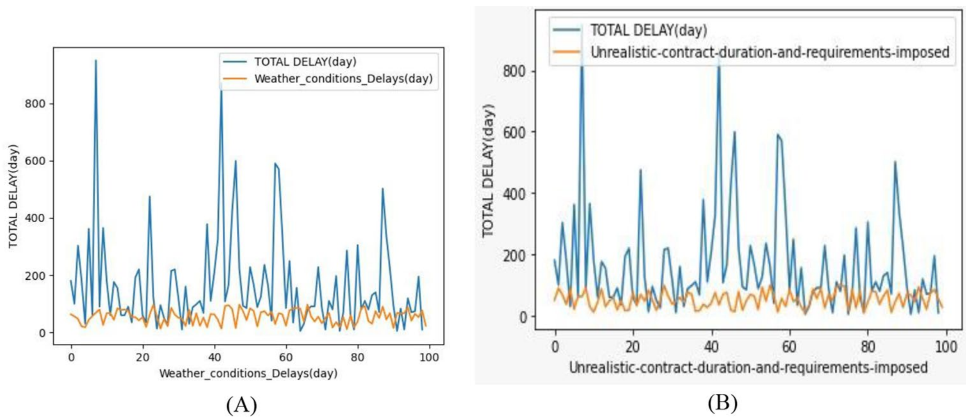

Fig. 3 Illustration of predicted data of the construction project delays. (in days) “Total Delay” and “Weather Conditions Delays” (A) Predicted correlation between and “Unrealistic Contract Duration and Requirements Imposed” (B) Predicted correlation between .(in days) “Total Delay”

GPR model results

Utilizing data analytics to make predictions on when potential issues may develop in construction projects is one strategy that might be used in order to mitigate the effects of the unavoidable issue of delays in such projects. This has ramifications for properly estimating the risk of delays in construction timeframes. It is important to emphasize that there is a dearth of pertinent historical data, which may serve as a barrier to the existence of such research. Given the information presented above, this study ought to be considered as an innovative and pioneering work in the area of anticipating delays in building projects.

In Fig. 2, paired scatter plots show feature-by-feature interactions. The plots with a diagonal shape depict histograms, which indicate the distribution of each variable’s probabilities. In the lower and upper triangles, scatter plots illustrate the relationships between the features. Each component is shown to demonstrate its distribution when used with the other features. A comparison of two scatter plots shows how one property has changed relative to another.

To establish a connection between the AHP model and the GPR model, the researcher must first extract new data from the original study data (191 projects). This new data must be equivalent to the percentage of data that pertains to weather conditions, unrealistic contract duration, and requirements that must be met.

The percentage of total delays in construction projects that can be attributed to weather-related factors is approximately 30%, which is consistent with the findings of the AHP model. Figure 3(A) illustrates the contribution of weather-related delays to overall delays. Figure 3(B) illustrates the contribution that unrealistic contracts have made to overall delays; the proportion that unrealistic contracts have contributed to overall delays is roughly 20%.

Figure 4 illustrates the expected delays (in days) for the overall delays under all of the delay factors (shown by the red line in the figure), the predicted delays under the weather circumstances (shown by the blue line in the figure), and the predicted delays under the fictitious contract (green line). As seen in this Figure, the anticipated delays caused by adverse weather conditions are more significant than those caused by an unrealistic contract, as shown by the AHP model findings. The figure also illustrates the contribution of weather-related delays to overall delays; approximately 30% of total delays in construction projects occur as a result of weather-related factors, and demonstrates the contribution of unrealistic contracts to overall delays; the percentage of unrealistic contracts to total delays is approximately 20%., which supports the findings of the AHP model.

The training model uses 5-fold cross-validation with a set loss function to record the outcomes for each step/loop. For parameter estimation, cross-validation is essential, and overfitting can be hard to prevent. Besides, the smoother features are regulated by the kernel’s width, usually stated in the

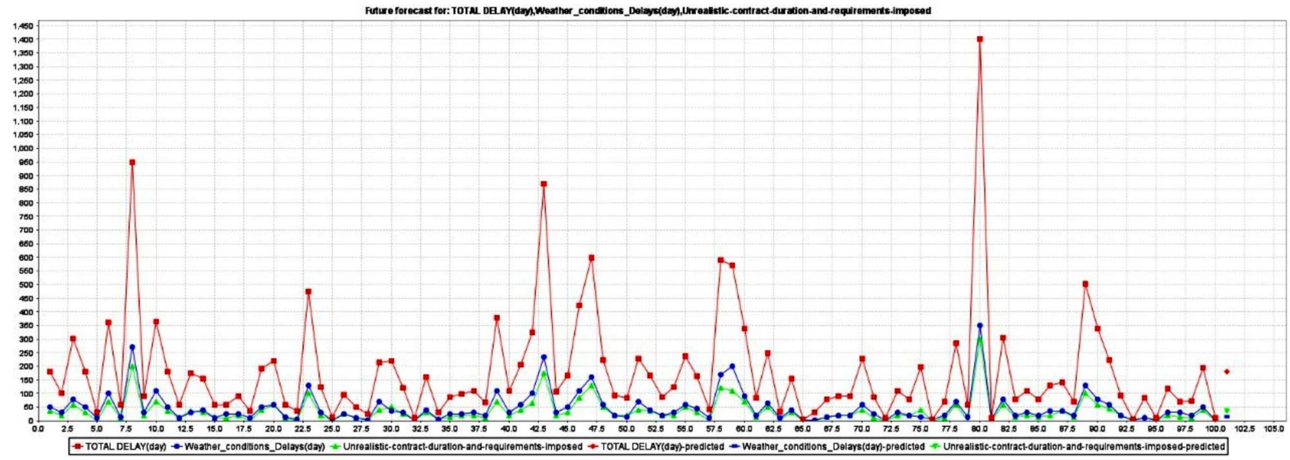

Fig. 4 Illustration of predicted value

neighboring count and cross-validated. The loop recorded each loss value of testing set points using mean square error. Then, the likelihood function and hyper-parameters optimization are defined to record the best sigma prior and length scale. Then, set up the testing data.

An illustration of results and comparing the losses to assess the model quality. Reporting the results and after hyperparameters Optimization, the length-scale(l_c), signal variance $(\sigma_p)$and the noise variance σ_n. This section shows standard GPR model results and an unknown GPR variance (model 2). Because we aim to get the optimum possible performance on a data set,

Figure 5 illustrates the connection between the variables and demonstrates that the AC has a negligible effect on the project data regarding time and cost overrun. This can be seen by looking at the graph. Nevertheless, the PD is the most crucial element and has a significant role in time overrun. As the value of a project declines, the PD examines the financial effectiveness and efficiency of the project, which in turn leads to the diminishing value of the time overrun. Because it is feasible to predict the cost overrun via planning, which contributes to the preparation of standards, the PD will have the most critical impact on the cost overrun. Because of this, there will be a significant reduction in the number of delays.

Gaussian Process Regression (GPR) is a form of supervised learning called kernelized Bayesian linear regression, where the kernel function and data guide the parameterization. GPR models learn a distribution between functions by estimating the mean and covariance functions at given points xxx. The predicted covariance depends on the kernel distance between training and test points, with the mean as a linear combination of observed target values weighted by these kernel distances. Figure 6 demonstrates advanced kernel engineering and hyperparameter tuning using gradient ascent on log-marginal likelihood.

This analysis uses data from government agencies, local authorities, companies, and engineering firms in Jordan. The model captures a long-term rising trend (34.4 ppm) with a 41.8-year length scale, a periodic component with a 1.44-year length scale, and white noise with a 0.197 ppm amplitude. The results show that the model accurately represents the data and makes precise predictions.

Figures 7 and 8 demonstrate that both approaches can learn realistic models of the target function. While KRR opts for the doubled periodicity, GPR determines that the periodicity of the function is approximately 6.28. GPR's analysis is correct. In addition, GPR offers adequate confidence bounds on the forecast, but KRR does not offer such options. The time needed to fit the data and make predictions significantly differentiates the two approaches. While fitting KRR can be completed quickly, the "curse of dimensionality" means that the grid search required to optimize hyperparameters takes an increasingly extended amount of time the more of them there are. This gradient-based optimization of the parameters in GPR does not suffer from this exponential scaling. As a result, it is significantly faster in this example with three-dimensional Hyperparameter space. The amount of time necessary to make a prediction is almost the same. However, the amount of time necessary to generate the variance of the predictive distribution of GPR is significantly longer than the amount of time necessary to predict the mean.

The remaining 10% of the data is then used to assess our model's predicting skills. Model testing results are provided in Table 3, which summarizes our results. The model's R2 values show that it can account for all phase angle variance. With this validation map, the study can see how well the model predicts the results of the related events. Calculates phase angle to within 0.01 degrees. This is the best-case situation because any point on the level of effort (LOE) shows that the model has correctly predicted the value.

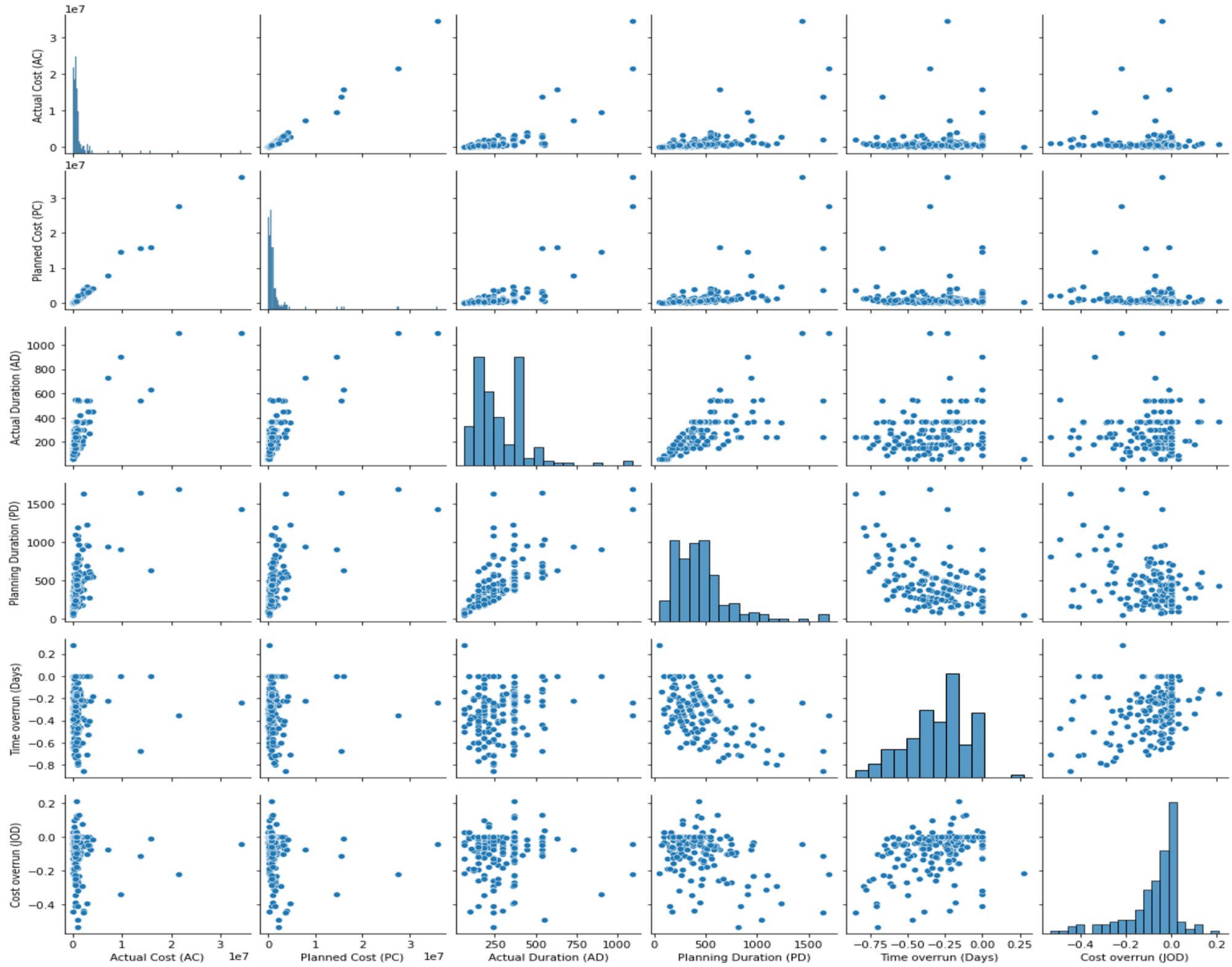

Fig. 5 The scatter map illustrates the relationship between the variables

Fig. 6 Five functions were derived from a Gaussian process with a mean of zero and a linear covariance function with the parameters set

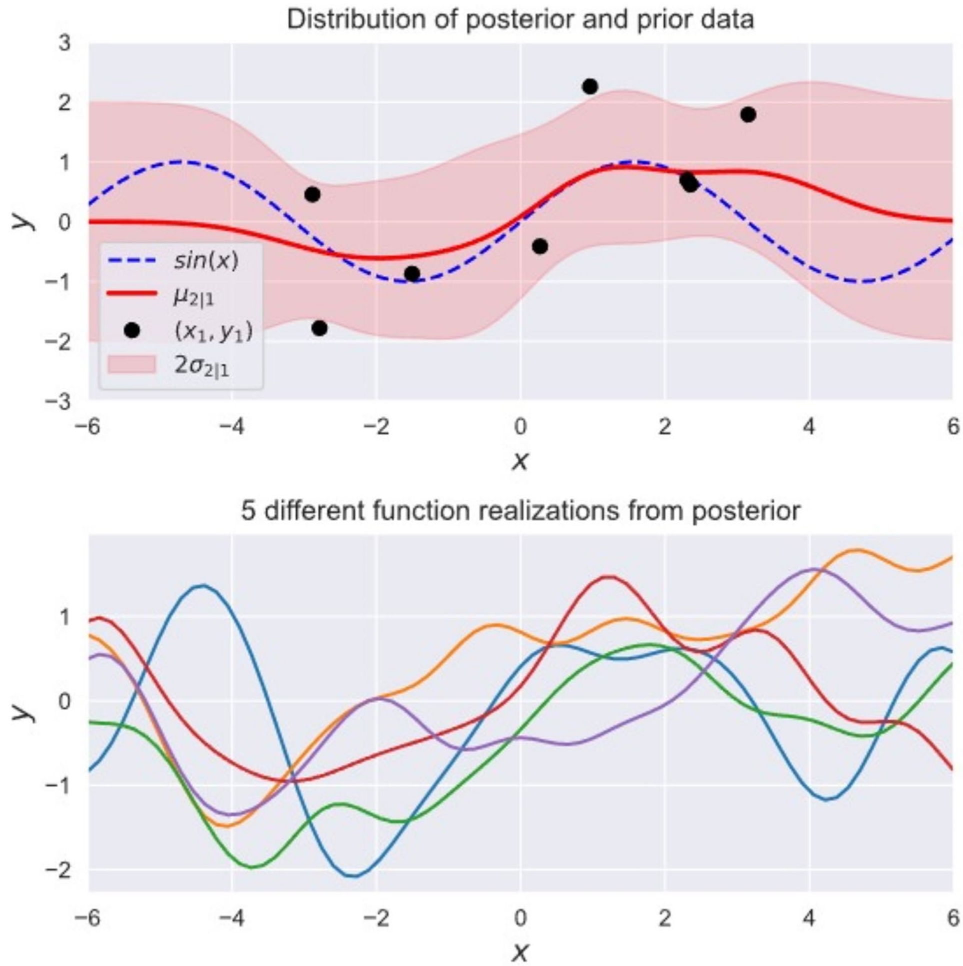

Fig. 7 Learning realistic models of the target function before data training

Discussion

Based on the study's results, the discussion emphasizes the implications and significance of employing both the Analytical Hierarchy Process (AHP) and Gaussian Process Regression (GPR) models to evaluate the impact of construction delays on project duration, particularly within the context of Jordanian construction projects. The AHP model provided a structured method for prioritizing factors contributing to construction delays. The findings revealed that weather conditions were the most significant factor, accounting for 27.73% of the total delay impact, underscoring the importance of considering environmental factors in project planning and execution (Çevikbaş & Işık, 2021). The second most critical factor was unrealistic contract duration and requirements, contributing 20.35%, highlighting the necessity of establishing realistic project timelines and clearly defined contract terms to mitigate delays (Odeh & Battaineh, 2002). Other significant factors included subcontractor practices and poor site management, emphasizing improved coordination and management within construction projects (Alsharef et al., 2021). The AHP model's ability to quantify the relative importance of various delay factors offers valuable insights for stakeholders, enabling them to focus on the most critical areas to reduce project delays (Sambasivan & Soon, 2007).

The GPR model demonstrated predictive solid capabilities, with a high R-squared (R^2) value of 0.98 after training, indicating its accuracy in predicting the impact of delays on project duration (Mahmoodzadeh et al., 2022). The GPR model's ability to handle nonlinear data through kernel functions effectively captured the complex relationships between various delay factors, with weather conditions again identified as having the most significant impact on time overruns, aligning with the AHP model's findings (Rasmussen, 2003). The success of the GPR model in predicting delay impacts with high accuracy suggests it can be a powerful tool for construction project managers in forecasting potential delays and making informed decisions to mitigate their effects (Gondia et al., 2020).

Integrating the AHP and GPR models offers a comprehensive approach to understanding and managing construction delays. While the AHP model provides a qualitative assessment and prioritization of delay factors, the GPR

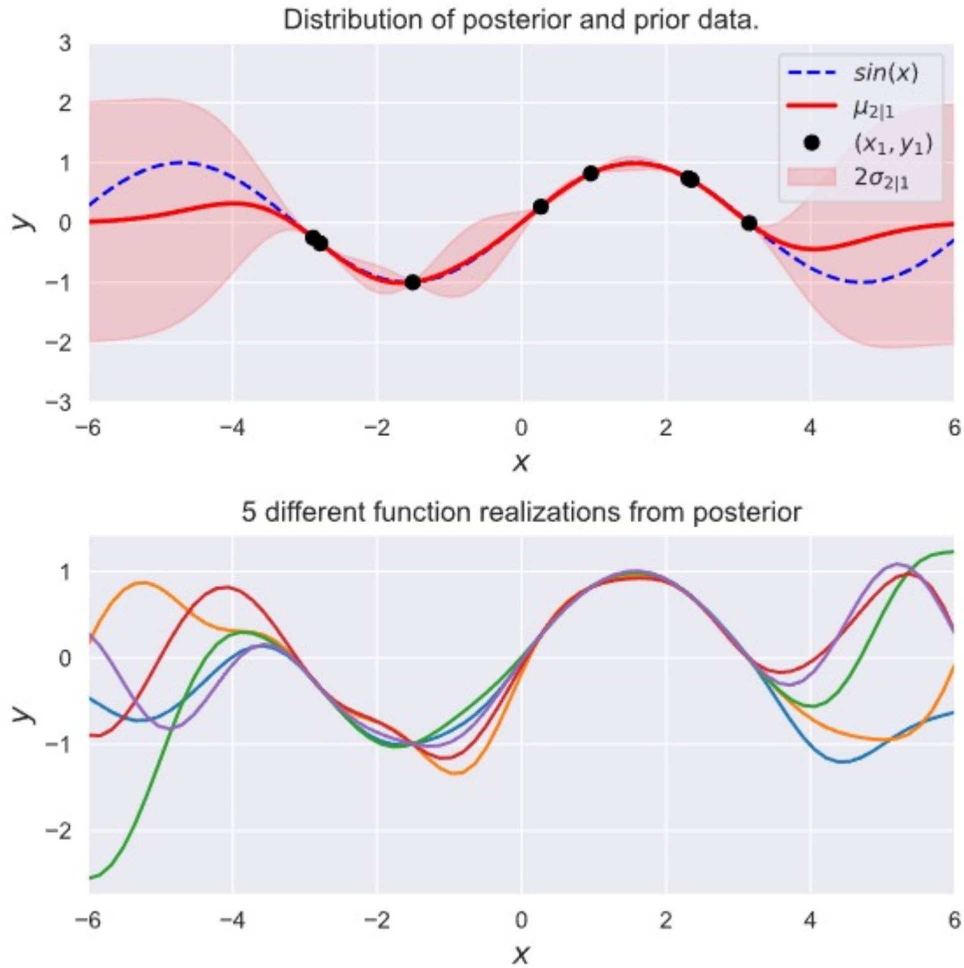

Fig. 8 Learning realistic models of the target function during data training

Table 3 Estimation losses with cross-validation loss method

Estimation losses with cross-validation loss method	Before training result	After training result
Mean squared error (MSE)	4.530e-17	4.525e-17
Mean absolute error (MAE)	3.691e-33	4.312e-33
Root mean squared error (RMSE)	6.567e-17	6.075e-17
R-squared (R^2)	0.82	0.98

model adds a quantitative dimension by predicting the extent of delays based on historical data (Li & Chen, 2018). This combination allows for more robust analysis, enabling project managers to accurately identify the most critical delay factors and accurately predict their impact on project timelines (Sanni-Anibire et al., 2021).

The study's findings have significant implications for the construction industry, particularly in regions like Jordan, where construction projects frequently face delays (Bekr, 2018). Accurately predicting and managing delays can lead to more efficient project execution, cost savings, and improved stakeholder satisfaction (Flyvbjerg, 2014). By adopting AI and machine learning techniques like GPR, alongside traditional decision-making tools like AHP, construction managers can enhance their ability to foresee and mitigate potential delays, ultimately leading to more successful project outcomes (Pan & Zhang, 2021).

Applying AHP and GPR models in this study has provided valuable insights into the factors contributing to construction delays and their impact on project duration. The integration of these models offers a powerful approach to predicting and managing delays, which can significantly improve project management practices in the construction industry. The findings suggest that project stakeholders should prioritize addressing weather-related issues and ensuring realistic contract terms to minimize the risk of delays (Arabiat et al., 2023).

Conclusion

The results of this study demonstrate the significant impact of various factors on construction delays, particularly in the context of Jordanian projects. Weather conditions and unrealistic contract durations were identified as the primary contributors to project delays, highlighting the critical need for more robust planning and risk management strategies. This study's successful application of the Analytical Hierarchy Process (AHP) and Gaussian Process Regression (GPR) models underscores their potential as powerful tools for predicting and managing delays. These findings validate the effectiveness of these models in capturing the complexities of construction projects and provide valuable insights for stakeholders aiming to reduce delays and associated costs.

Despite the promising results, this study has several limitations that should be addressed in future research. The analysis was constrained by the availability of historical data, which may have influenced the accuracy of the predictions. Additionally, while the study focused on crucial delay factors, other potential variables influencing project timelines were not explored. Future work should aim to expand the dataset and incorporate a broader range of factors to enhance the predictive accuracy of the models. Moreover, further research could explore integrating other machine learning techniques to improve the robustness and adaptability of delay prediction models in diverse construction environments.

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Declarations

Competing interests The authors declare no competing interests.

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with a financial or non-financial interest in the subject matter or materials discussed in this manuscript.

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