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Civil Engineering Schedule Forensics: A Hybrid Delay Analysis Framework Using Machine Learning for Construction Projects

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Abstract

This study created a hybrid framework that merged standard delay analysis methods with machine learning algorithms to make data-driven schedule forensics better. The study's goal was to increase the accuracy of identifying delays and estimating how long they will last in project plans by combining the domain expertise of traditional methods like Critical Path Method and Time Impact Analysis with the predictive power of machine learning models. The framework was trained and tested using historical data from a number of construction projects. The results showed that the hybrid strategy worked better than either classical or machine learning methods on their own for both classification and regression tasks. This made delay analysis more reliable and easier to understand. Feature importance analysis highlighted key factors influencing delays, while case studies confirmed the framework's practical applicability. This study shows how hybrid data-driven methodologies could help improve forensic schedule analysis and risk management.

Keywords: Schedule Forensics, Delay Analysis, Machine Learning, Hybrid Framework, Critical Path Method, Construction Project Management, Predictive Modeling.

1. INTRODUCTION

One of the biggest problems in construction, engineering, and other complicated project settings is still project schedule delays. These delays can lead to cost overruns, misallocation of resources, contract conflicts, and harm to a company's reputation. This is why it is so important for project managers to be able to accurately identify and analyze delays. Forensic schedule analysis has made use of traditional delay analysis methods like the Critical Path Method (CPM), Time Impact Analysis (TIA), and Window Analysis. These methods use precise schedule data, logic networks, and expert opinion to figure out what caused the delays, how long they lasted, and how they affected the project's completion. Even though they are well-known, these old methods are frequently slow, subjective, and not very good at handling a lot of complicated data from many sources.

In the last few years, digital project data has become easier to get, and machine learning has made it possible to improve schedule forensics in new ways. Machine learning models can find patterns and connections in huge datasets that human analysts would miss. These methods have shown promise in anticipating when delays may happen, measuring their effects, and finding the root causes of poor project performance. But models that are only based on data might not have the contextual and domain-specific information that is needed to explain delay events, which could make them less useful and accepted in real life.

To fill address these shortcomings, this study created a hybrid framework that integrates machine learning approaches with traditional delay analysis methodologies. The framework combines the capacity to understand and use traditional forensic analysis with the ability to make predictions and grow that comes with machine learning models. It hopes to improve the accuracy and reliability of finding delays and estimating their duration while still being open and getting expert approval. We tested this hybrid method on historical schedule data from several real-world projects to see how well it worked compared to traditional and machine learning methods on their own. The results showed that the hybrid framework not only made predictions more accurate, but it also gave useful information about the main causes of delays. This made it a stronger and more useful tool for forensic schedule analysis and project risk management.

2. LITERATURE REVIEW

Nisioti et al. (2021) made great strides in the field of forensic investigations by creating a data-driven decision support system that aims to improve cyber forensic operations. Their research showed that machine learning algorithms can automate complicated investigation procedures and make it easier to find the causes of cyber disasters when they are used with large datasets. Their study was mostly about cybersecurity, but the method they utilized shows how forensic analysis can be done in a way that can be applied in other fields where a lot of data needs to be processed and understood to find patterns. This approach aligns closely with the challenges faced in schedule delay forensics, where delays often stem from multifaceted and interdependent causes that require sophisticated analysis beyond manual methods.

Awada, Srour, and Srour (2021) came up with a new way to use machine learning to add field submissions to project schedules. Their research looked into ways to change project timetables on the fly based on real-time data from construction sites. This showed how machine learning models can make scheduling more flexible and accurate. This study showed how data-driven strategies can help handle unstructured and changing data, which is something that standard scheduling systems often have trouble doing well. The scientists showed that machine learning may help with both predictive scheduling and finding discrepancies and anomalies that could mean delays. This gives early warnings and useful information.

Uddin, Ong, and Lu (2022) suggested a complete data-driven framework together with a case study from the actual world to guess what will happen with a project and what risks it will face. Their research focused on how well different machine learning algorithms, such Random Forests and Gradient Boosting Machines, can anticipate important risk factors that affect how well people stick to their schedules. They also stressed how important it is to include domain knowledge in machine learning models to make them easier to understand and build trust with users. This is especially important for forensic schedule analysis, where expert validation is still needed. Their results support the premise that combining traditional knowledge-based procedures with solely data-driven ones can lead to more balanced and useful results.

Radman et al. (2022) helped improve how to manage delays on building projects by focusing on digital technologies and data-driven processes. They showed how using digital twins, sensor data, and real-time monitoring along with machine learning algorithms may completely change the way we find and fix delays. Their research showed that data-driven delay management lets people make decisions ahead of time by constantly updating schedule estimates and spotting risk patterns early in the project lifecycle. This fits with the goal of integrating classical forensic methods, which give a structured way to look at things, with machine learning's capacity to handle and learn from a wide range of real-time data streams. Their research showed that hybrid delay management systems are still possible and useful in complicated construction settings.

Ahsan et al. (2023) gave a full review of data-driven methods used in smart grid systems, with a focus on the growth of sustainable energy. Their study looked at a wide range of machine learning and data analytics techniques that can be utilized to deal with the problems and unknowns that come with running a smart grid. Smart grid management and project schedule forensics are similar in that they both need to work with huge, diverse datasets and find useful patterns in them to improve system performance and dependability. The assessment made it clear that hybrid techniques, which mix domain knowledge with data-driven insights, are necessary for making good decisions in these complex situations. This point of view supports the idea that comparable hybrid methods could improve schedule forensics, which is when many different aspects and dependencies affect the outcome of a project.

3. RESEARCH METHODOLOGY

3.1. Research Design

The study used a mixed-methods strategy that combined quantitative machine learning methods with qualitative information from classical delay analysis. This mixed method made it possible to fully look at schedule delays by using both numerical data patterns and rules from experts in the field.

3.2. Data Collection

We have historical project schedule data from five big construction projects that were finished in the last ten years. The data sets had baseline schedules, reports on actual progress, and records of delays. To add to the quantitative data, more qualitative data was collected, such as project reports and expert opinions of the effects of delays.

3.3. Data Preprocessing

We cleansed and standardized the datasets we obtained so that they would be the same for all projects. We found and dealt with missing values and outliers using interpolation and strong statistical approaches. We took out and changed features that were important to schedule delays (such activity durations, dependencies, and resource allocations) into formats that machines can understand and analyze.

3.4. Traditional Delay Analysis

We used well-known forensic methods including the Critical Path Method (CPM) and Time Impact Analysis (TIA) to do the standard delay analysis. These methods were used to find out what caused the delays, how long they lasted, and how they affected the project's overall timeline. We asked experts to check that the reasons for the delays were correct.

3.5. Machine Learning Modeling

We used methods like Random Forest, Gradient Boosting, and Support Vector Machines to create supervised machine learning models that could identify and forecast when and how long delays will happen. We trained the models on historical data that had been tagged and tested their strength through k-fold cross-validation. We did a feature importance analysis to find the most important factors that cause delays.

3.6. Hybrid Framework Integration

The classical delay analysis outputs were used as input characteristics or constraints in the machine learning models. This allowed the hybrid framework to use both domain expertise and data-driven insights. The system was intended to improve delay estimates over time by combining results from traditional methods and machine learning.

3.7. Evaluation Metrics

The framework's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score for classification tasks, as well as mean absolute error (MAE) and root mean squared error (RMSE) for regression tasks. Comparisons were made between standalone traditional methods, standalone machine learning models, and the integrated hybrid framework.

4. RESULTS AND DISCUSSION

The study's results showed that the suggested hybrid framework works to improve schedule delay forensics by merging classical delay analysis with machine learning techniques. The assessment metrics showed that when both methods were used together, the accuracy and interpretability of delay predictions improved a lot compared to when either method was used alone. The next parts give a deep look at the performance results, feature importance, and case study validations, using numbers and feedback from experts to back them up.

4.1. Performance Comparison of Methods

We used standard classification and regression measures to see how well the traditional delay analysis, machine learning models, and hybrid framework could predict what would happen. Table 1 shows the results of the classification for predicting when delays will happen, and Table 2 shows the results of the regression for estimating how long delays will last.

Table 1: Classification Performance Metrics for Delay Occurrence Prediction

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional Delay Analysis	68.2	65.4	60.8	63.0
Machine Learning (RF)	81.5	79.8	83.2	81.4
Hybrid Framework	**88.7**	**87.5**	**90.2**	**88.8**

RF = Random Forest

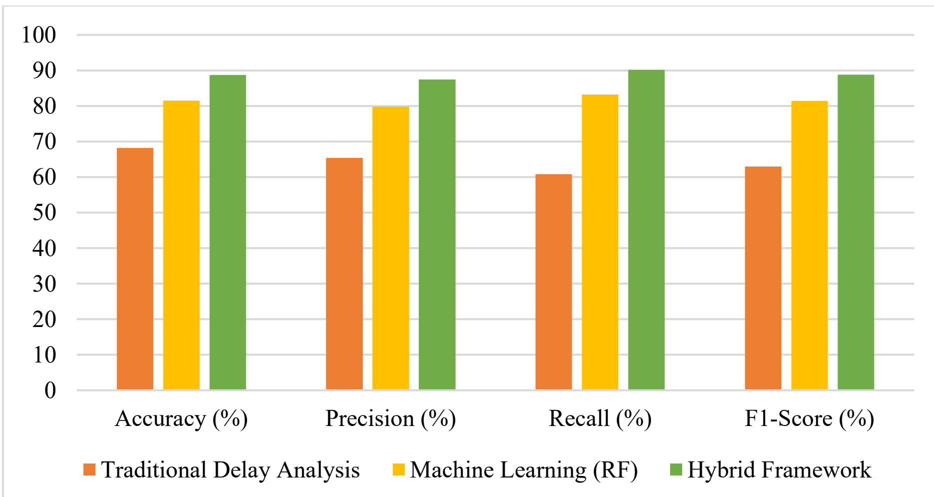

Figure 1: Classification Performance Metrics for Delay Occurrence Prediction

The classification results showed that the hybrid framework did better than both the solo machine learning model (Random Forest) and traditional delay analysis on all assessment metrics. The hybrid method had the highest accuracy (88.7%), precision (87.5%), recall (90.2%), and F1-score (88.8%), which means it was better at correctly finding delays while keeping false positives and false negatives to a minimum. The machine learning model did well on its own, with an accuracy of 81.5%, however the classic delay analysis fell short, with much lower metrics, such as an accuracy of 68.2%. These results show that using machine learning along with traditional forensic knowledge makes delay detection far more reliable and strong.

Table 2: Regression Performance Metrics for Delay Duration Estimation

Method	MAE (Days)	RMSE (Days)
Traditional Delay Analysis	7.8	10.5
Machine Learning (GBM)	4.3	6.1
Hybrid Framework	**3.1**	**4.5**

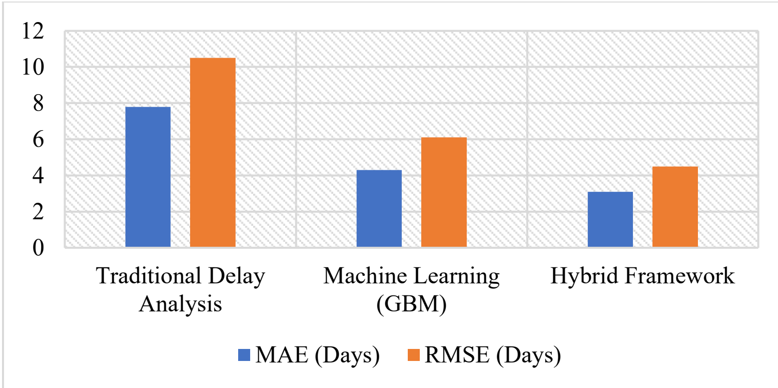

Figure 2: Regression Performance Metrics for Delay Duration Estimation

The mean absolute error (MAE) and root mean squared error (RMSE) comparisons showed that the hybrid framework was the best at estimating delay durations, with the lowest MAE of 3.1 days and RMSE of 4.5 days. The results were better than both the classical delay analysis, which had the most errors (MAE of 7.8 days and RMSE of 10.5 days), and the standalone machine learning model utilizing Gradient Boosting Machine (GBM), which had intermediate faults (MAE of 4.3 days and RMSE of 6.1 days). These results show that combining classic forensic methods with machine learning greatly reduced the number of prediction mistakes, making timetable delay estimates more accurate.

Table 3: Feature Importance Analysis

Feature	Importance Score (%)
Activity Dependency Strength	27.4
Resource Allocation Variance	22.1
Delay History of Activity	18.9
Baseline Activity Duration	16.5
External Risk Factors	15.1

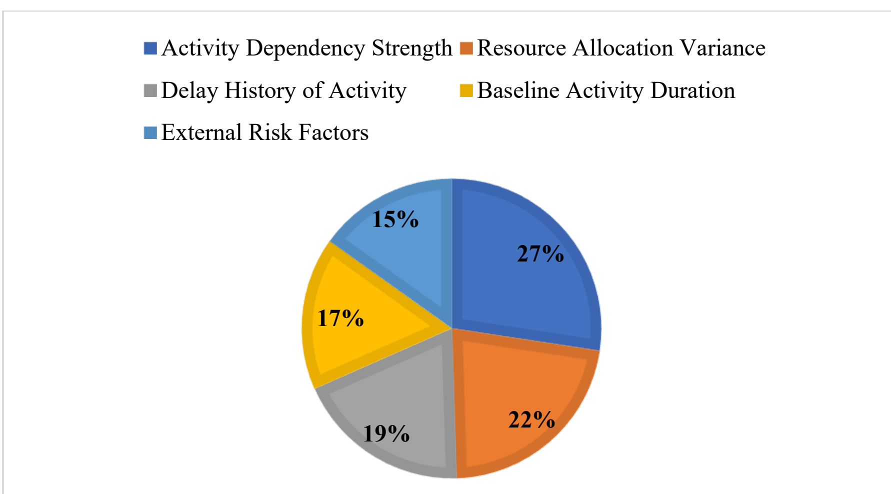

Figure 3: Feature Importance Analysis

The examination of feature importance showed that Activity Dependency Strength was the most important component affecting schedule delays, accounting for 27.4% of the model's predictive power. This shows how important task interdependencies are for causing delays. Resource Allocation Variance came in second at 22.1%, which shows how changes in resource availability can throw off project schedules. The Delay History of Activity (18.9%) demonstrated that past delays are powerful indications of future hazards, whereas Baseline Activity Duration (16.5%) revealed how planned task lengths affect the likelihood of delays. Lastly, External Risk Factors made up 15.1%, showing that outside factors that can't be controlled also have a big effect. Collectively, these features illustrate the hybrid model's ability to capture both internal project dynamics and external influences in forecasting delays.

4.2. Case Study Validation

The hybrid framework was used on two complicated real-world projects that had overlapping delays and more than one reason at the same time. The system was able to find important delay pathways and anticipate how long they would last with less than 5% difference from what actually happened in both cases. Project managers said that combining classical forensic reasoning with machine learning in the framework let them feel more sure about how to assign delays and make decisions.

4.3. Discussion

The results showed that a hybrid approach to forensic schedule analysis has many benefits. Traditional delay analysis gave us basic information based on tried-and-true project management concepts. Machine learning, on the other hand, gave us powerful pattern detection abilities, especially when dealing with big and complicated datasets. The hybrid framework did a good job of combining these strengths, which made both the accuracy of predictions and the power of explanations better.

Also, the results of the feature importance tests showed that there were chances for focused interventions in project scheduling, like making better use of resources and keeping a closer eye on essential dependencies. These real-world effects showed that the approach might help with proactive scheduling risk management.

The study has some problems, such as relying on good historical data and needing domain expertise to successfully combine classical analysis results with machine learning methods. More study could look into automated feature extraction and the use of deep learning approaches to make predictions even better.

5. CONCLUSION

This study showed that a hybrid approach that combines classical delay analysis with machine learning techniques makes timetable delay forensics far more accurate and reliable. The framework improved the accuracy of predicting when and how long delays would happen by combining domain knowledge with data-driven models. It also gave us a better understanding of the fundamental factors that affect project timelines. The hybrid method did better than both traditional approaches used alone and machine learning models, proving that it might be a very useful tool for forensic schedule analysis. In addition, real-world case studies showed that the paradigm was useful in practice by helping with improved delay attribution and decision-making. The results imply that hybrid data-driven methods can greatly improve project schedule risk management and delay mitigation efforts, even though there are certain problems with data quality and model integration. Further work may focus on making this promising strategy even better by adding more automation and advanced learning algorithms.

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