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RESEARCH ARTICLE

Synergizing Global and Local Strategies for Dynamic Project Management: An Advanced Machine Learning-Enhanced Framework

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ABSTRACT In this study, we introduce a versatile and scalable optimization tool designed to address several critical project management needs. Our aim is to provide project managers with a robust decision support system that enhances and streamlines decision-making processes. Building upon our previously proposed global scheme—which optimizes project schedules by adjusting dates to match each task's optimal period—we introduce a novel local scheme. This innovative addition leverages a Machine Learning pipeline, specifically utilizing the Silverkite algorithm, to facilitate long-horizon forecasting. By synergistically combining global and local optimization strategies, we elevate project management efficiency, maximizing potential benefits. This tool is equipped to handle a wide array of variables, offering real-time, consultative support throughout the project's lifecycle. Through the demonstration of various scenarios, we showcase the effectiveness and adaptability of our optimization tool, underscoring its value in contemporary project management contexts.

INDEX TERMS Artificial intelligence in project management, decision support systems, resource allocation optimization, dynamic project management.

I. INTRODUCTION

In recent years, there is an ever-increasing trend in exploring the benefits of Artificial Intelligence in the field of Project Management, as the tools and techniques associated with this technology can ensure higher cost-effectiveness, efficient project planning and efficiency within the business environment. Critical infrastructures, such as transport networks and hubs, power grids, communication and information systems, serve as the backbone of modern society, supporting essential services and economic activities. Any disruption or inefficiency within these infrastructures can have far-reaching consequences, impacting local communities and regional and global economies.

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In modern critical infrastructure management, integrating advanced project management methodologies with cutting-edge business intelligence capabilities is a linchpin for sustainable success [1]. As critical infrastructures navigate through an era characterized by rapid technological advancements and intelligent services, evolving user demands, and pressing environmental concerns, adopting innovative project management frameworks becomes imperative [2]. This paper underscores the significance of managing critical infrastructure projects and emphasizes the need to leverage business intelligence to facilitate a sustainable transition within this dynamic industry. By synergizing global and local strategies, the scope of the methodology framework is to provide a comprehensive solution tailored to the unique challenges faced by critical infrastructures, addressing the need for the exploration of a dynamic and adaptable framework designed to optimize project management processes within the context of critical infrastructures, in the face of complex and ever-changing demands.

This paper addresses the key concept of dynamic project management, particularly as it relates to IT infrastructure project planning and management. Dynamic project management emphasizes flexibility, responsiveness, and adaptability when handling projects with frequent changes and uncertainties. This approach is crucial for IT infrastructure projects, where rapid technological advancements, evolving user requirements, and unforeseen challenges are common.

In the context of IT infrastructure, dynamic project management involves continuously monitoring and updating project plans, leveraging real-time data and analytics to make informed decisions. It integrates agile methodologies, which allow for iterative progress and incremental delivery of project components. This ensures that the project can adapt to new information and shifting priorities. This adaptability is essential for maintaining project alignment with business goals and stakeholder expectations.

Furthermore, dynamic project management in IT infrastructure projects enhances risk management by proactively identifying potential issues and implementing mitigation strategies. This proactive stance reduces the likelihood of disruptions and ensures smoother project execution. It also facilitates better resource allocation, optimizing personnel, budget, and technology to effectively meet project objectives.

Building on these foundational concepts, the following section details the key contributions of our proposed framework in addressing the unique challenges critical infrastructures face. The primary contribution of our framework lies in the innovative combination of several key features, which together create a robust and flexible tool for project management:

- **Project-Agnostic Design**: Our framework is designed to be universally applicable across various types of projects. It can generalize easily to different domains, providing flexibility and adaptability. This project-agnostic nature ensures that the framework is not limited to specific project characteristics or industries, making it a versatile tool for diverse project management needs.
- **Highly Modular Structure**: The framework allows users to define and prioritize numerous critical tasks and task types. Users can customize the importance of each task type by adjusting associated weights, ensuring that the optimization process aligns with each project's unique priorities and constraints. This modularity addresses the need for tailored project management solutions, accommodating modern projects' complex and dynamic nature.
- **Forecasting capabilities**: One of the standout features of our framework is its ability to incorporate machine learning-based forecasting. This is particularly valuable when the optimal periods for critical tasks cannot be determined solely through existing expert knowledge. By predicting future trends and values with high precision, the framework helps project managers anticipate and strategically plan for future challenges and opportunities. This forecasting capability ensures that projects can be managed effectively and efficiently even under uncertainty.
- **Synergistic Integration of Global and Local Optimization**: Our framework integrates global and local optimization strategies, adapting dynamically to the project's evolving needs. The global optimization sets the overarching project timeline, while the local optimization fine-tunes specific tasks in response to real-time changes and disruptions. This dual approach ensures that both high-level project goals and detailed execution plans are optimized, improving overall project performance.

These contributions collectively address several critical needs in project management. By providing a flexible, adaptable, and highly customizable tool, our framework enhances the ability of project managers to plan and execute projects efficiently, even in the face of uncertainty and complexity. Integrating advanced forecasting techniques further adds to its utility, making it an invaluable asset for modern project management.

II. RELATED WORK

Integrating AI techniques in the business process has led to the development of smart project management monitoring systems and Decision Support Systems (DSS), which can boost decision-making quality by assisting project managers and executives in the strategic and operational decision-making process [3]. Knowledge-based Dynamic Decision Support tools can positively impact Cost and Efficiency Key Performance Indicators, ensuring scheduled delivery, optimized project scheduling, and risk reduction. In terms of current research, Bang and Olsson [4] performed a systematic scoping review which showed that Estimation and cost control is the area of application with the most scientific research papers (22%), followed by Logistics, planning and scheduling (19%). Consequently, 41% of the current research of Artificial Intelligence applications in project management is focused on project planning, project scheduling, logistics and cost control and estimation.

Bo and Ting [5] developed a model-based Decision Support System for project managers to effectively solve the problem of how to control the schedule and human resources of a software product development start-up company. Results showed that successfully implementing such tools and techniques can significantly impact achieving budget and time constraints. However, the application of such technologies is not yet widely used in the industry due to its emerging nature. Integrating Decision Support systems in the modern business environment with no previous exposure to these tools also requires an appropriate selection of a specific project management methodology for the organization to have a smooth adaptation and extract the maximum benefit of Artificial Intelligence-based Decision Support Systems. According to Najdawi and Shaheen [6], an organization willing to adapt to the realm of AI transformation in the field of project management is likely to focus on Agile approaches, particularly the Scrum framework, which incorporates a faster pace towards a digital transformation. Taroum and Yang [7] developed a unique assessment methodology that enables assessing the risk impact of specific project objectives using risk cost as a common scale by employing the Dempster-Shafer theory of evidence (DST) and the Evidential Seasoning (ER) approach innovatively. In addition, this study devised a spreadsheet-based decision support system to facilitate the proposed approach.

Another very important factor in construction in project management is the effective implementation of risk strategies and risk management planning. The increasing number of studies conducted in the field of risk modelling and assessment shows that the integration of dynamic risk assessment and analysis into flexible decision-support systems can minimize the cost at risk in a construction project and facilitate a smoother decision-making process [8]. In addition, according to the study of Oluleye et al. [9] the adoption of Artificial Intelligence for enhancing the implementation of systemic circularity in the construction industry has 13 applications domains, namely a; material selection, b; design for waste prevention, c; technical and economical circularity, d; hazardous materials prediction, e; operation of circular business models, f; estimation of BCDW generation, g; onsite waste recycling, h; pre-demolition in auditing a CE, k; materials strength prediction for reuse and recycling post-EOL, k; reverse logistics in BCI, l; missing BCDW data management and analysis, m; optimization of waste collection and site selection for BCDW recycling plant. Riaz and Husain [10] developed an Intelligent Decision Support System (IDSS) for monitoring construction projects by employing Learning Vector Quantization (LVQ) for data clustering. It aims to enhance decision-making in construction management by organizing and analyzing data for quick decision support. The research involves comparative analysis with standard algorithms through case examples, demonstrating the application of various data mining techniques. The research emphasizes the importance of technology in every step of construction management, highlighting the challenge of data organization for effective decision support and the potential of LVQ in classifying projects into defined categories for better management outcomes. Liu and Hao [11] introduced a novel approach to forecasting scheduling issues in engineering project management by employing deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). It focuses on accurately predicting project characteristics, including successors and renewable resource requirements, by analyzing historical data from real-life engineering projects. The findings demonstrate that LSTM and GRU models can significantly reduce forecasting errors, contributing to more efficient project scheduling and resource allocation. The study also highlights the reliability and robustness of these models in addressing dynamic scheduling challenges, offering valuable insights for project management practices. Zhu and Huang [12] introduced an advanced resource scheduling method for enterprise management, leveraging artificial intelligence and deep learning. It focuses on the enhanced particle swarm algorithm applied on a cloud deep learning platform to tackle the virtual and physical machine mapping problem. The study demonstrates significant efficiency improvements in enterprise operations, showcasing a 35% increase in efficiency and a 20% reduction in personnel compared to traditional methods. A MATLAB simulation confirms the method's scientific validity and effectiveness, offering a novel approach to optimizing enterprise resource scheduling and management in the context of global economic competition and project management challenges. Lischner and Shtub [13] introduce a dynamic machine learning (ML) tool leveraging an Artificial Neural Network (ANN) to enhance project duration predictions across diverse organizational types and datasets. By training the ANN model with varied architectures and utilizing a genetic algorithm for optimization, the tool adapts to different prediction methods and datasets, offering significantly improved accuracy. Validation with real-life project datasets from two distinct organizations demonstrated the tool's effectiveness, with notable advancements in prediction accuracy compared to traditional methods, showcasing its potential for broad applicability in project management. Anagnostopoulos and Koulinas [14] introduced a genetic hyperheuristic algorithm designed to address the resource-constrained project scheduling problem (RCPSP), a significant challenge in project management due to its NP-hard nature. The algorithm controls a set of low-level heuristics for effective resource allocation, aiming to minimize project delays and budget overruns. Through computational experiments with randomly generated projects, the algorithm demonstrates promising results in finding good solutions within a reasonable timeframe. This novel approach, implemented in commercial project management software, showcases the potential of genetic hyperheuristics in optimizing project schedules under resource constraints. Khambhammettu and Persson [15] study presented an optimization-based decision support system for enhancing operating room (OR) resource planning and surgery scheduling. A simulation experiment evaluated the proposed model using real-world data from a local hospital. The results demonstrated significant improvements in scheduling efficiency, including reduced surgery turnover times, increased OR utilization, and minimized idle times, compared to actual schedules at the hospital. The optimization-driven decision support system offers a robust analytical framework for surgery scheduling, potentially improving resource allocation and operational efficiency in healthcare facilities.

Iluz and Shtub [16] explored the effectiveness of Simulation-Based Training (SBT) in enhancing trade-off analysis and decision-making within lean development environments, specifically for systems engineers and project managers. Utilizing the Project Team Builder (PTB) simulator, an innovative tool for project management and system engineering training, the study examines whether SBT can yield clearer insights into project trade-offs and improve decision-making skills. The findings of controlled experiments and field studies suggest that SBT significantly improves trade-off analysis and decision-making, offering valuable implications for project management and systems engineering education and practice. Salling and Leleur [17] developed a novel framework for evaluating transport projects by integrating feasibility risk assessment and scenario forecasting with traditional Cost-Benefit Analysis (CBA). The proposed Reference Scenario Forecasting (RSF) method incorporates Optimism Bias adjustments and employs Monte Carlo simulations to model project cost and demand forecast uncertainties. Scenario forecasting further enriches this approach to account for varying economic growth and integration levels. By applying this methodology to the case of a fixed link between Elsinore, Denmark, and Helsingborg, Sweden, the study demonstrates the RSF's capability to provide a more nuanced and probabilistic understanding of project viability, highlighting its potential as a robust decision-support tool in transport infrastructure planning. Greehna and Edayadiyil [18] introduce an automated system for monitoring construction progress through machine learning and image processing. It focuses on masonry work but is adaptable to various construction activities. Utilizing a dataset of 356 images from multiple construction sites, the system employs a supervised CNN classifier for brickwork recognition with notable accuracy and recall rates of 81% and 83%, respectively. This innovation offers a platform for automatic construction monitoring and a systematic approach to data collection, aiming to replace manual monitoring methods and enhance decision-making processes in construction management. Wang and Hu [19] research paper presented a deep learning-based artificial intelligence (AI) technology application in building construction management system modeling. It introduces a 3D reconstruction deep learning model, integrates it with Building Information Modeling (BIM) for construction progress reliability control, and designs functional modules for progress monitoring, reliability early warning, and prediction. Utilizing case simulations, the study demonstrates how AI technology can enhance the efficiency of construction schedule management, offering significant advantages in operating costs and ease of use and promoting AI application during the construction phase. Sharma and Al-Hussein [20] study introduces a framework for an Asset Levels of Service (ALOS)-based decision support system aimed at optimizing municipal infrastructure investments, particularly in maintenance, rehabilitation, and repair (MR&R) activities. Emphasizing the allocation of funds based on ALOS, future demand, and interdependencies among infrastructure networks, the research underscores the complexity of infrastructure asset management due to cost escalation, increasing demand, and network interconnections. The framework leverages utility functions, Multi-objective analysis, and analytical techniques to guide funding decisions, enabling municipalities to address chronic funding shortfalls and efficiently maintain infrastructure service levels.

Vasiliev and Goryachev [21] explored the use of text mining methods within the realm of artificial intelligence to address challenges in project management. It emphasizes the significance of processing vast amounts of unstructured textual data generated during project execution, including documents and participant communications. By extracting valuable, previously unknown information from these data arrays, text mining technology aids in achieving project objectives more efficiently. The study covers the technology's fundamentals, current approaches, and methods, highlighting its potential to enhance decision-making and project performance through informed analysis. Finally, Karki and Hadikusumo [22] study developed a predictive model to identify competent project managers in Nepal's construction sector using supervised machine learning. Auditing expert opinions and survey data validated fifteen competency factors, and project managers were assessed on their competency levels. The Waikato Environment for Knowledge Analysis (WEKA) tool was employed to predict project manager performance as "Higher than expected," "Expected," or "Lower than expected." The Sequential Minimal Optimization (SMO) classifier demonstrated the highest accuracy, with personal characteristics, leadership skills, and communication skills significant predictors of competency. This research improves project success rates by facilitating the selection of competent managers through an AI-based approach.

Bredael and Vanhoucke [23] focus on resource-constrained multi-project scheduling (RCMPSP), evaluating ten meta-heuristic algorithms using a novel dataset. Their study is significant for its comprehensive benchmark analysis which reveals the varying effectiveness of these algorithms based on different optimization criteria and project deadlines. Their work provides insights into the strengths and weaknesses of each algorithm, emphasizing the importance of selecting the right approach based on specific project constraints and objectives. In another study, Guo and Zhang's [24] research paper reviews multi-objective optimization (MOO) applications in construction project management. They perform a analysis and a qualitative review, highlighting the increasing use of MOO to enhance project outcomes in areas such as project planning, risk management, and structural health monitoring. This study underscores the growing relevance of MOO in managing the multifaceted objectives of modern construction projects, such as improving constructability, safety, and cost-effectiveness.

Furthermore, Kebriyaii et al. [25] introduced a genetic algorithm that handles the time-cost-quality trade-off in project scheduling, considering the fuzzy nature of activity durations typical in construction projects. Including fuzzy logic allows for a more flexible and realistic modeling of project scheduling uncertainties. Kebriyaii et al.'s approach demonstrates how integrating fuzzy parameters can lead to better handling of uncertainties, resulting in more robust project management strategies. Similarly, Luong et al. [26] explored multi-objective, multi-mode resource-constrained project scheduling in prefabricated building construction. They propose an Opposition-based Multiple Objective Differential Evolution (OMODE) algorithm, which significantly enhances the ability to manage and optimize projects under the complex constraints of prefabricated construction. Their work addresses the challenge of scheduling with multiple conflicting objectives and emphasizes the practical benefits of their approach through a case study involving a highway construction project. Last but not least, Rahman et al. [27] also introduced a memetic algorithm for solving the RCPSP, highlighting its efficiency in exploring and exploiting the solution space. By integrating various heuristics and local search mechanisms, their approach effectively handles the resource constraints and precedence relations among activities, demonstrating potential for significant improvements in project scheduling efficiency.

To sum up, integrating complex mathematical models and algorithms, from metaheuristics, genetic algorithms, and differential evolution to ML and Deep Learning algorithms, plays a critical role in addressing the multi-dimensional aspects of project scheduling. These models provide the flexibility and robustness needed to handle various uncertainties and dynamic conditions of modern projects. In addition, a common denominator across the aforementioned studies is the emphasis on multi-objective optimization, which is crucial for balancing conflicting objectives such as time, cost, and quality. As a result, the ability to optimize across multiple criteria simultaneously leads to more comprehensive and effective project management strategies.

III. THE PROPOSED APPROACH

Our methodology embraces a dynamic and adaptable framework designed to optimize project management processes, integrating two distinct but synergistic global and local strategies. The scope of this manuscript is to present an efficient approach to managing project tasks. While the work is not exhaustive regarding algorithms, it represents a refined attempt to enhance project management using well-known optimization tools and approaches. We elevate these tools by combining global optimization before the project starts with local optimization during its execution, creating a more robust and comprehensive process. This framework's universality is a key feature, as it is not confined to any specific project domain, allowing users to tailor their solutions to the unique characteristics of each project. The global scheme is pivotal in establishing an overarching project timeline, meticulously adjusting the entire project calendar to align with optimal dates for executing critical tasks, thereby ensuring strategic alignment of project milestones with periods conducive to maximum productivity and minimal disruption. Concurrently, the local scheme offers a more granular approach to optimization, which is particularly valuable in scenarios necessitating replanning due to unforeseen delays or when detailed activity optimization is required. This targeted strategy is especially adept at managing dynamic tasks influenced by external factors—such as market volatility or resource fluctuations—that significantly affect the project's cost-effectiveness.

Our approach incorporates a machine learning (ML) pipeline to navigate the uncertainties associated with these dynamic tasks, predicting future trends and values with remarkable precision. This dual-faceted strategy, underpinned by sophisticated ML insights, empowers project managers to recalibrate specific project segments in real-time and anticipate and strategically plan for future challenges and opportunities. By harmonizing comprehensive timeline optimization with the flexibility to adapt to evolving project landscapes, our methodology offers a robust solution for achieving both the strategic objectives and operational efficiencies required for successful project management in today's complex and dynamic environment.

To clarify and highlight, the global scheme's purpose is to adjust the entire project calendar within a predetermined range to enhance the alignment between the actual dates of tasks and their optimal schedules. Conversely, the utility of the local scheme is limited to the duration of the project's execution, meaning it is not feasible to shift the entire calendar as the project is already underway. In this context, we introduce the concept of **flexibility**, defined as the maximum delay the project can accommodate from the point of optimization. By integrating flexibility into the optimization process, we enable the algorithm to potentially extend the duration of a task when deemed beneficial, thereby optimizing its overall performance and outcome.

A. GLOBAL SCHEME

The global strategy is designed to organize the project's schedule and optimize the execution plan for maximum efficiency and benefit. Users or project coordinators must submit a detailed Gantt chart outlining the project's execution plan, including start and end dates, durations, and dependencies between activities. Additionally, they must identify which tasks warrant optimization and specify the optimal periods for them, categorizing each task as budget-related or weather-dependent. This classification is important as it allows for assigning weights to each task, enabling a tailored approach to optimization where priorities can be adjusted based on the significance of budgetary constraints or weather conditions to the project's success.

After collecting the necessary data, the global scheme pipeline is deployed to fine-tune the project calendar. This optimization is achieved using the dual-annealing algorithm, paired with a custom scoring function that determines the optimal adjustments to the schedule. Dual annealing is a global optimization algorithm that merges the features of simulated annealing, which has been effectively used in project management and decision-making, with a local search strategy. Simulated annealing is referenced in several studies [28], [29], [30] for its effectiveness in these domains. Dual annealing is a demonstration tool and can be substituted with any comparable optimization method. For our experiments, we utilized the SciPy[1] implementation of dual annealing, treating it as a black-box optimizer. This scoring function is specifically designed for tasks identified for optimization and evaluates two main aspects: Firstly, it assesses how well the scheduled periods of tasks align with the optimal periods specified by the user. This involves comparing the planned task dates in the Gantt chart against the user-defined ideal timeframes, ensuring that tasks occur at the most opportune moments. As it can be depicted in the equation 1

Given a specified date range and an array representing the optimal period for a task, we aim to calculate the normalized overlap between these intervals. This normalization quantifies the alignment of the task's execution window within the desired scheduling window, crucial for optimizing project timelines and resources.

To this end, all dates are converted to `datetime64` format, ensuring consistency and precision. We then determine the start and end points of the intersection between the specified date range and the optimal period array, representing the actual overlap.

The formula for calculating the Dates Overlap index, Dates Overlap(i), is refined as follows:

$$\text{Dates Overlap}(i) = \frac{\max(0, E_i - S_i)}{D_{\text{opt}}} \tag{1}$$

where:

- $S_i = \max(S, S_{\text{opt}})$, the later start date between the task's start (S) and the optimal period start (S_{opt}).
- $E_i = \min(E, E_{\text{opt}})$, the earlier end date between the task's end (E) and the optimal period end (E_{opt}).
- $D_{\text{opt}} = E_{\text{opt}} - S_{\text{opt}}$, the total possible number of days within the optimal period, from its start to end.

This formula yields a normalized score between 0 and 1, where 1 indicates a complete overlap between the specified range and the optimal period, and 0 indicates no overlap. This metric assists in evaluating the feasibility and timing of project tasks relative to their optimal scheduling windows.

$$\text{Maximize} \sum_i \left(\text{Dates Overlap}(\text{Task}_i) \times \text{Weight}_i\right) \tag{2}$$

B. LOCAL SCHEME

The local optimization strategy is invoked in scenarios of significant delays or when project managers consider replanning due to enhanced insights into task execution acquired during the project's lifecycle. This process parallels the global scheme using the current date and task status as a baseline to optimize the remaining schedule. A distinctive feature of the local scheme, setting it apart from the global approach, is its emphasis on incorporating dynamic tasks—particularly those influenced by volatile factors such as fluctuating market prices. Our methodology adeptly manages these tasks, offering a reliable forecast of future values with commendable accuracy.

For such tasks, a machine learning pipeline is employed to predict future values, further enhancing the project's adaptability and responsiveness to changing conditions. This feature is especially crucial for projects where external factors such as market trends or environmental conditions can significantly impact task execution and project outcomes. The dynamic tasks do not need an optimal period definition, as the static tasks used in the global scheme; the ML pipeline is responsible for producing accurate long-horizon forecasts, which the optimization will leverage to maximize the score function.

The optimization of dynamic tasks assesses the gap between the optimal price period (over the original duration of the tasks) and the selected one from the optimization output based on the forecasted value. It critically examines if scheduling these dynamic tasks aligns with periods of advantageous pricing, thereby optimizing cost efficiency. This insight is invaluable for enhancing project cost-effectiveness, as it facilitates accurate predictions of future prices, guiding project managers on strategic decisions for the project's remainder. Beyond this, the optimization mirrors the global scheme, revisiting crucial tasks that may have deviated from their optimal timelines as initially outlined in the global plan, ensuring a thorough re-evaluation of the best execution dates.

$$\begin{aligned}\text{Prices Overlap} &= \frac{\text{Best Pricing Window}}{\text{Selected Pricing Window}} \\ &= \frac{BPW}{SPW}\end{aligned} \tag{3}$$

where:

- BPW (Best Pricing Window) is the time frame offering the most advantageous pricing, where window = Original Task Length.
- SPW (Selected Pricing Window) is the time frame chosen for pricing based on specific criteria or strategy.

$$\begin{aligned}\text{Maximize} \sum_i \Big(&\text{Dates Overlap}(\text{Task}_i) \times \text{Weight}_i \\ &+ \text{Prices Overlap}(\text{Task}_i) \times \text{Weight}_i\Big)\end{aligned} \tag{4}$$

Access to these optimization schemes empowers project managers to strategically plan projects, considering their unique priorities. The utility of our tools is twofold, offering significant advantages:

- **Immediate Application of Optimized Gantt Charts**: The primary benefit is generating an optimized Gantt chart. This chart can be directly implemented as the

[1] https://scipy.org/

new project plan. It integrates with the project manager's inputs regarding prioritization and optimization criteria, ensuring the plan aligns with the project's specific goals and constraints.

- **Insightful Analysis for Strategic Re-evaluation**: The local and global outputs provide critical insights into the project's scheduling. These insights may prompt users to review the project's timeline and task dependencies thoroughly. Such a review can lead to the strategic rearrangement of tasks, leveraging the opportunity to further enhance project outcomes. This iterative process acts as a feedback loop: project managers input their preliminary plans, and our tool evaluates and refines these plans, offering insights that positively influence the project's direction.

IV. EXPERIMENTS

The research paper uses the port of Agios Konstantinos, situated in the central region of Greece, as the focal point for investigation. This port is a crucial maritime transportation hub, boasting four terminals and a designated parking facility catering to vehicles and motorcycles. Its principal function revolves around facilitating ferry routes to the Sporades region. Notably, the port can host up to four ferry boats and two large fishing vessels, underscoring its pivotal role in the local transportation network.

The construction endeavor at the port of Agios Konstantinos encompasses a comprehensive scope, comprising 35 distinct activities and is anticipated to transpire over a span of 24 months. A salient aspect of this undertaking is the substantial portion of construction work, approximately 80%

Two primary parameters control the trajectory of activities within this project: weather conditions and budget allocations. These variables have a significant influence on the project's progression and eventual outcomes. Project Contract

The contractual agreement for the construction project at the Agios Konstantinos port was formalized on February 26, 2020, stipulating a predetermined duration of 24 months. A total budget of *euro*4,058,732 has been earmarked for the execution of this project. It is imperative to note that the project remains ongoing, with various phases and activities currently underway. Figure 1 provides a depiction of the port.

Three pivotal milestone dates delineate the project, each marking a critical phase in its execution timeline:

- 1. Setting of Boulders - Foundation (Scheduled for 6 months after project initiation)
- 2. Construction & Installation of Cobblestones (Expected to reach completion at the 9-month juncture from project initiation)
- 3. Completion of the Superstructure (Envisaged upon reaching the 12-month milestone from project initiation)

These milestones serve as significant markers delineating the progress and evolution of the construction project at the port of Agios Konstantinos.

The experiments were carried out within the construction timeline for the Port of Agios Konstantinos in Greece. This setting allowed us to explore and illustrate various scenarios under both global and local frameworks, providing a comprehensive view of project management's potential outcomes and strategies.

A. GLOBAL SCHEME EXPERIMENTS

We began with the project's original schedule in the global scheme and specifically identified four tasks.[2] for optimization. We manually established an optimal period for each task as a hypothetical exercise, simulating scenarios where expert guidance would typically inform such decisions. This approach allows us to exemplify the calibration of critical tasks based on hypothetical, expert-like input, albeit generated through our manual process.

Our methodology further entails categorizing tasks according to their susceptibility to weather conditions or potential impact on the project's budget. Through three distinct cases, we illustrate how shifting the entire calendar can enhance alignment between the original timelines of tasks and their manually set optimal periods. Despite using the same schedule and optimal periods across cases, we varied the weightings to show the impact of these adjustments on scheduling outcomes. Importantly, our approach is adaptable, supporting various weight types and tasks. The scenarios provided are intended to demonstrate the flexibility and effectiveness of our method, not to limit its application to these specific examples.

In the sequel, a detailed analysis of the results for each optimization case is given.

1) CASE 1: WEIGHT–{BUDGET=0.8, WEATHER=0.2}

In the first scenario, budget considerations were given priority with a weight of 0.8, in contrast to weather considerations at 0.2. This emphasis on cost efficiency led to a schedule shift of 66 days. The focus on budget management enabled schedule optimization while maintaining minimal weather-related delay impacts. Consequently, the project's completion time was moved by 66 days, offering potential cost reductions.

This case demonstrates that by prioritizing budget constraints, we were able to optimize the schedule while keeping the impact on weather-related delays relatively low. The project's completion date was reduced by 66 days, potentially resulting in cost savings due to earlier completion.

2) CASE 2: WEIGHT–{BUDGET=0.5, WEATHER=0.5}

In the second scenario, budget and weather considerations received equal importance, each receiving a weight of 0.5. This balanced approach resulted in a schedule shift of 83 days. By equally weighting budget and weather, the project's end date was advanced by 83 days from the original

[2]The tasks were identified through interviews with project managers involved in the case study project.

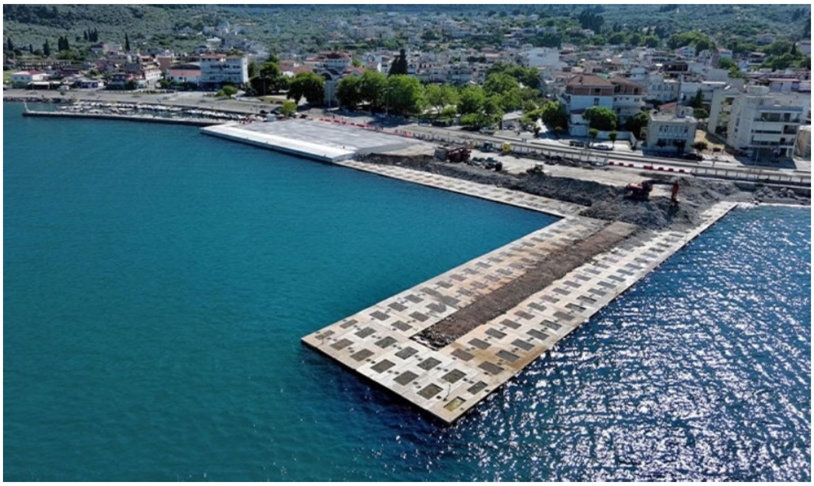

FIGURE 1. Front view of the port of Agios Konstantinos.

TABLE 1. Task Schedule (Before Optimization).

Task	Early Start	Early Finish	Late Start	Late Finish	Optimal Period	Type
Subsea Bottom Excavations	14/4/2020	3/7/2020	11/6/2020	1/8/2020	28/08-30/11	Weather
Road Pavements	22/9/2021	22/9/2021	25/10/2021	25/10/2021	01/07-31/08	Budget
Construction of Synthetic Drainage Systems	3/7/2020	22/8/2020	12/7/2020	26/11/2020	01/10-31/01	Budget
Construction of boulders	3/8/2020	20/2/2021	20/2/2021	20/2/2021	01/10-28/02	Budget

TABLE 2. Task Schedule (Case 1: Weight - {Budget=0.8, Weather=0.2}).

Task	Early Start	Early Finish	Late Start	Late Finish	Optimal Period
Subsea Bottom Excavations	19/6/2020	7/9/2020	16/8/2020	6/10/2020	28/08-30/11
Road Pavements	27/11/2021	27/11/2021	30/12/2021	30/12/2021	01/07-31/08
Construction of Synthetic Drainage Systems	7/9/2020	27/10/2020	16/9/2020	31/1/2020	01/10-31/01
Construction of boulders	8/10/2020	27/4/2021	27/4/2021	27/4/2021	01/10-28/02

plan, illustrating an effective compromise between managing costs and mitigating weather uncertainties.

In this case, we balanced budget control and weather-related delays. The project's completion date was reduced by 83 days compared to the initial schedule. This approach ensures cost control while also considering weather-related uncertainties.

3) CASE 3: WEIGHT—{BUDGET=0.2, WEATHER=0.8}

In the third case, the emphasis shifted towards weather considerations, weighted at 0.8, versus a lower budget consideration at 0.2. This prioritization led to an extensive schedule adjustment of 121 days. By focusing more on minimizing weather-related delays, the algorithm favored weather-related tasks, highlighting an approach designed to lessen the impact of weather disruptions on the project timeline.

In this case, we achieved a significant schedule adjustment of 121 days by giving higher importance to weather-related delays. This approach aims to reduce weather-related disruptions

B. LOCAL SCHEME EXPERIMENTS

The local scheme, while bearing close resemblance to the global one, distinguishes itself by accommodating dynamic tasks. We have engineered a machine learning (ML) pipeline for these tasks that delivers accurate forecasts. To demonstrate the efficacy of our method, we have integrated a dynamic task—the Road Pavements activity—into our analysis. This task, from September 22, 2021, to October 25, 2021, is a practical example. Our primary aim is to enhance the cost-efficiency of the project by deriving predictive insights into the future price movements of asphalt, thereby informing budgetary decisions and optimizing resource allocation.

To effectively illustrate our methodology, the ML system is utilized to forecast for 6-month horizons to encompass potential adjustments for the road pavement project to test diverse scenarios. This approach leverages the original task schedule, without the global optimization, to inform our planning. Notably, as detailed in Table 1, which enumerates all critical tasks, road pavement is scheduled last. Optimizing this task involves applying Equation 4, focusing solely on the second term for price overlaps.

TABLE 3. Task Schedule (Case 2: Weight - {Budget=0.5, Weather=0.5}).

Task	Early Start	Early Finish	Late Start	Late Finish	Optimal Period
Subsea Bottom Excavations	6/7/2020	24/9/2020	2/9/2020	23/10/2020	28/08-30/11
Road Pavements	14/12/2021	14/12/2021	16/1/2021	16/1/2021	01/07-31/08
Construction of Synthetic Drainage Systems	24/9/2020	13/11/2020	3/10/2020	17/2/2021	01/10-31/01
Construction of boulders	25/10/2020	14/5/2021	14/5/2021	14/5/2021	01/10-28/02

TABLE 4. Task Schedule (Case 3: Weight - {Budget=0.2, Weather=0.8}).

Task	Early Start	Early Finish	Late Start	Late Finish	Optimal Period
Subsea Bottom Excavations	13/8/2020	1/11/2020	10/10/2020	30/11/2020	28/08-30/11
Road Pavements	21/1/2022	21/1/2022	23/2/2022	23/2/2022	01/07-31/08
Construction of Synthetic Drainage Systems	1/11/2020	21/12/2020	10/11/2020	27/3/2021	01/10-31/01
Construction of boulders	2/12/2020	21/6/2021	21/6/2021	21/6/2021	01/10-28/02

1) MODEL SELECTION

In the context of time-series forecasting, cross-validation is a critical method for assessing the predictive performance of models. It involves segmenting the time-series data into training and test sets, then systematically training the model on one segment and validating it on another. Given the sequential nature of time-series data, care is taken to maintain the chronological order during this process.

This paper assesses a suite of time-series models—each with distinct forecasting strategies. These models range from simpler ones like Naive and HWES (Holt-Winters Exponential Smoothing), to more complex ones like ARIMA (AutoRegressive Integrated Moving Average), Silverkite, LightGBM, XGBoost, and Prophet. For each model, a grid search is performed to optimize hyperparameters, and a methodical exploration of a range of hyperparameters is performed to identify the combination that minimizes the forecasting error. The performance metric used to gauge the efficacy of the models is the Root Mean Square Error (RMSE), which measures the magnitude of the forecasting error, allowing for the comparison of model accuracy across different forecasting horizons.

The cross-validation process ensures that each model is tuned for optimal parameter settings and tested for its generalization capability—how well it can perform on unseen data. This approach is particularly well-suited for time-series data, which aims to predict future values based on past observations. This process's rigor helps identify the most reliable and accurate model for forecasting the time-series data under study. After comprehensive hyperparameter optimization via grid search, the best settings for each time-series forecasting model were identified. These models were then applied to predict over an approximate six-month daily horizon, with Figure 2 and Table 5 illustrating their test set performance.

The analysis reveals Silverkite as the standout, showcasing significant forecasting precision improvement, as evidenced by its Test Set RMSE of 25.38. This indicates a strong model fit during training, effectively carrying over to unseen data. HWES also displayed commendable performance, with a relatively lower Test Set RMSE, signifying its reliability and simplicity over more complex models. Despite a higher

TABLE 5. Model performance.

Estimator	In-Sample RMSE	Test Set RMSE
Silverkite	29.53	25.38
HWES	2.39	32.22
GBT	5.12	56.55
ARIMA	8.96	60.04
XGBoost	2.12	68.52
Naive	32.94	70.98
LightGBM	11.51	73.94

test set RMSE, ARIMA improved markedly from its in-sample performance, demonstrating the cross-validation's role in boosting model adaptability. Although proficient in learning from historical data, Prophet exhibited limitations in forecasting accuracy, hinting at potential challenges in capturing complex data patterns. Naive and LightGBM, with the highest RMSEs, might have suffered from overfitting or failed to adequately model the data's seasonal and trend dynamics.

2) LOCAL SCHEME SCENARIOS

a: SCENARIO 1—SINSIGHTS-BASED SCENARIO

The first scenario presents a straightforward situation where optimization is not required, as the project proceeds according to plan without extending the timeline. This context provides the project manager with valuable insights ahead of a forthcoming dynamic task. By examining the forecasted data for two specific periods—the window from July 1, 2021, to December 31, 2021, depicted in Figure 3, and the period from September 22, 2021, to March 23, 2022, shown in Figure 4—the project manager can make informed decisions regarding the timing of asphalt purchases. A detailed analysis of these figures indicates that procuring the asphalt earlier can lead to significant cost savings. This scenario underscores the importance of strategic planning and the benefits of leveraging predictive insights to optimize resource allocation and project expenditure.

b: SCENARIO 2—REPLANNING DUE TO PROJECT'S DELAY

In the second scenario, we explore two distinct cases relevant to replanning. The remaining schedule can be depicted in

TABLE 6. Remaining schedule after replanning.

Task	Early Start	Early Finish	Late Start	Late Finish	Requires Optimization
Road pavements	22/9/2021	25/10/2021	22/9/2021	25/10/2021	✓
Construction of asphalt layers	25/10/2021	25/11/2021	25/10/2021	25/11/2021	×
Transportation of Lighthouse	26/11/2021	27/11/2021	26/11/2021	27/11/2021	×
Other constructions	25/11/2021	26/11/2021	24/12/2021	24/12/2021	×
Fences	24/12/2021	27/12/2021	25/1/2020	29/1/2022	×
Site uninstallation	31/1/2022	31/1/2022	25/2/2022	25/2/2022	×

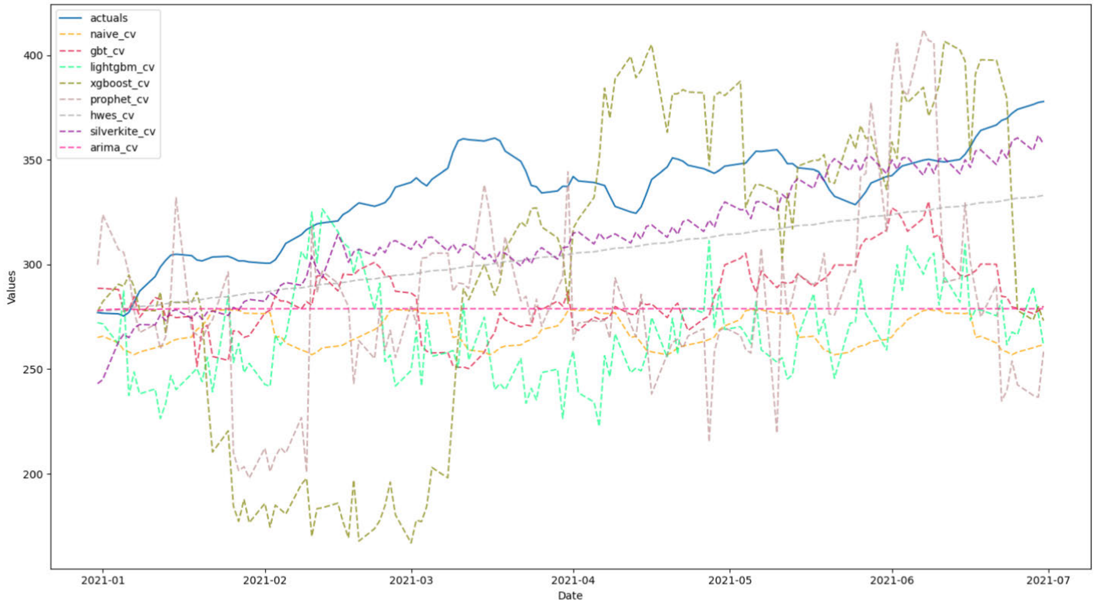

FIGURE 2. Test set performance.

FIGURE 3. 6-month Forecasting window from July 1, 2021 to January 1, 2022.

Table 6. The initial case occurs with a delay of 40 days compared to the original plan, where we can extend the project duration by up to two months, consequently adjusting the overall timeline. Figure 6 provides a six-month forecasting window for this scenario, illustrating how project adjustments might impact planning. As we consider extending the task,

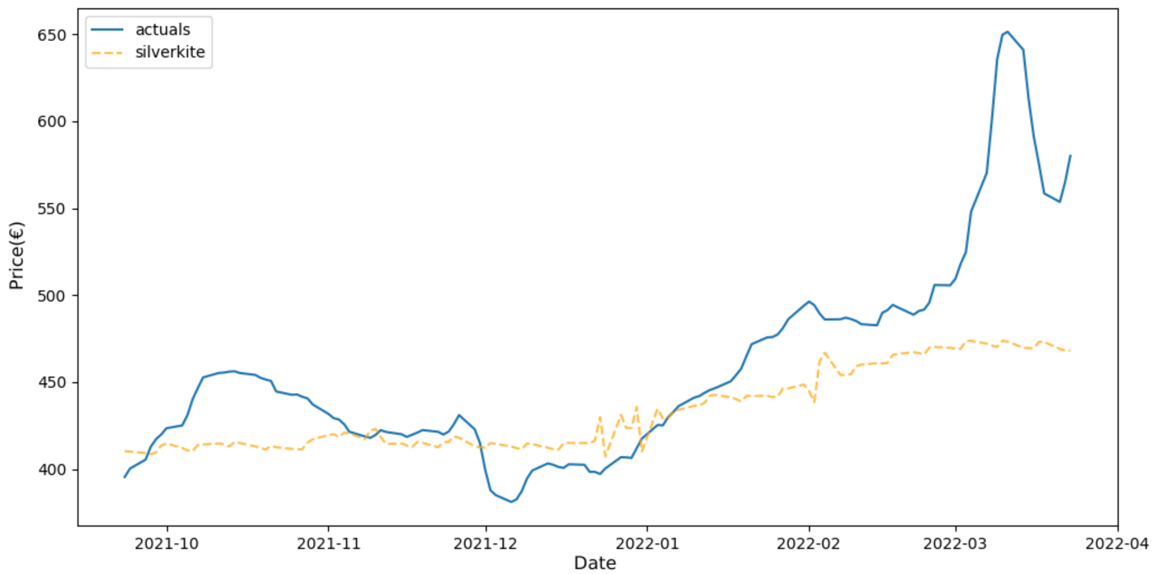

FIGURE 4. 6-month forecasting window from September 22, 2021 to March 23, 2022.

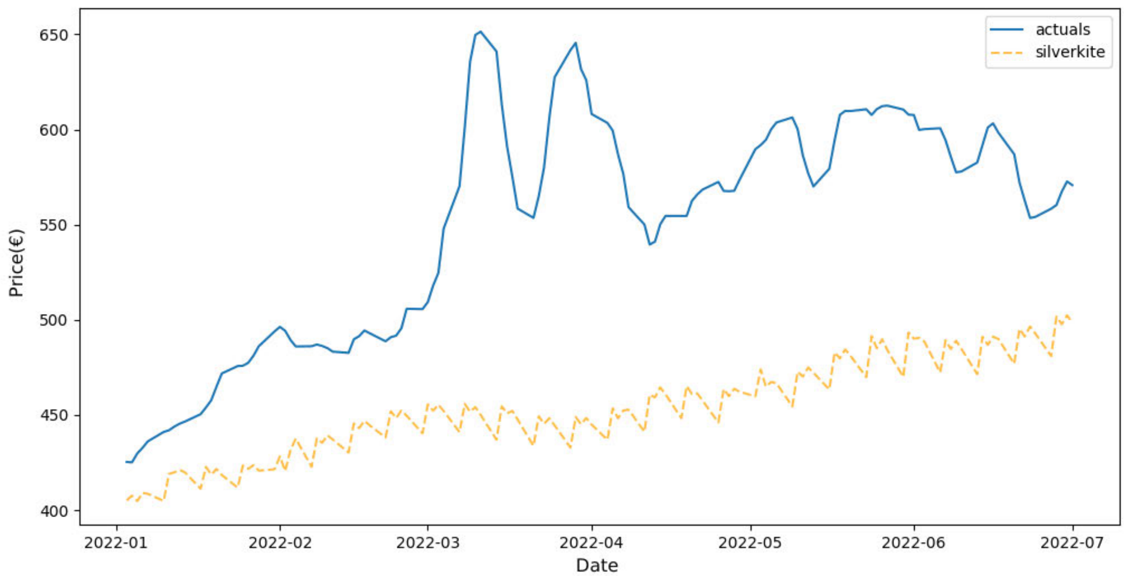

FIGURE 5. 6-month Forecasting window from January 1, 2022 to July 1, 2022.

TABLE 7. Pending optimization tasks - Case 2 {Delay = 40 days | Flexibility = 2 months}.

Phase	Task	Early Start	Late Start	Early Finish	Late Finish	Optimal Period
Before Optimization	Road pavements	1/11/2021	4/12/2021	1/11/2021	4/12/2021	-
	Site uninstallation	12/2/2022	12/2/2022	10/3/2022	10/3/2022	15/3 - 30/3
After Optimization	Road pavements	20/11/2021	23/12/2021	20/11/2021	23/12/2021	-
	Site uninstallation	4/3/2022	4/3/2022	30/3/2022	30/3/2022	15/3 - 30/3

the optimal price window remains unchanged, although the current pricing strategy hinges on the average of selected dates. Accordingly, the optimization algorithm aims to extend the task duration to a juncture that minimizes costs, according to Equation 2. The algorithm's output aligns with forecasted prices, recommending a 19-day extension to optimize financial efficiency.

The second case involves a significant delay of approximately 100 days, necessitating a shift in the project start date from September 22, 2021, to January 1, 2022. A review of

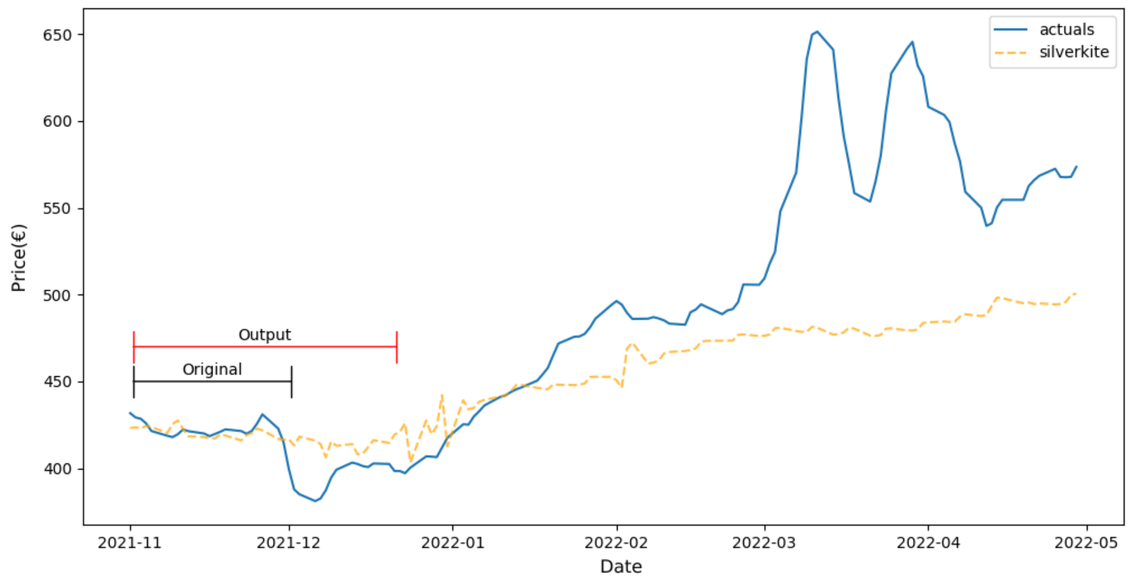

FIGURE 6. 6-month Forecasting window from November 11, 2021 to April 1, 2022. We also showcase the original timeframe of the task versus the suggested window from the optimization output.

TABLE 8. Pending optimization tasks - Case 2 {Delay = 101 days | Flexibility = 2 months}.

Phase	Task	Early Start	Late Start	Early Finish	Late Finish	Optimal Period
Before Optimization	Road pavements	1/1/2022	1/1/2022	3/2/2021	3/2/2021	-
	Site uninstallation	11/5/2022	11/5/2022	5/6/2022	5/6/2022	15/6 - 30/6
After Optimization	Road pavements	1/1/2022	3/2/2021	1/1/2022	3/2/2021	-
	Site uninstallation	5/6/2022	5/6/2022	30/6/2022	30/6/2022	15/6 - 30/6

the forecasted window shown in Figure 5, clearly indicates that extending the project duration is unnecessary. On the contrary, any increase in the task period is likely to incur higher costs due to a marked upward trend in asphalt prices. Consequently, the optimization algorithm advises against any extension, suggesting an adjustment of 0 days to mitigate financial risk and capitalize on the most cost-effective timing.

c: SCENARIO 3—REPLANNING DUE TO PROJECT'S DELAY OPTIMIZING DYNAMIC AND STATIC TASKS

In the third scenario, we build upon the two cases outlined in the second scenario, adding a static task: the Site Uninstallation task which follows the Road Pavements task. We retain the flexibility of adjusting the project timeline by up to two months. Revisiting Equation 4, the first part is incorporated as the optimization contains a static task. Specifically, extending the duration of the Road Pavements task not only affects its own timeline but also shifts the timeframe of the Site Uninstallation task. Consequently, the optimization algorithm must now account for the impact of these adjustments on both tasks.

The outcome of this more intricate optimization exercise for the first case mirrors the recommendation from scenario two, suggesting an extension of the Road Pavements task by 19 days. However, the Site Uninstallation task is additionally recommended to be prolonged by 14 days. Table 7 presents the dates before and after the optimization procedure while the forecast again refers to Figure 6. This strategy aims to maximize the overlap between the tasks and the identified optimal period, thereby enhancing the overall efficiency and cost-effectiveness of the project. On the other hand, the second case corresponding to Figure 5 suggests keeping the dynamic task unaltered as the pricing trend seems to be increasing while moving the static task by 24 days to maximize the overlap of the dates with the optimal period.

V. CONCLUSION AND FUTURE WORK

In conclusion, our study presents a novel optimization tool that significantly advances project management practices. By integrating a global scheme for comprehensive calendar optimization with a local scheme incorporating advanced Machine Learning forecasting, we offer a dynamic solution to project managers' complex challenges. Including the Silverkite algorithm within our tool's framework enables precise long-horizon forecasting, enhancing decision-making accuracy and efficiency. Even though our framework is very adaptable, it necessitates the optimal periods of tasks to function effectively. If the optimal periods can be inferred through the dynamic strategy, it still requires relevant data and careful forecast horizon selection, as this can significantly impact the results . Our approach facilitates an efficient alignment of project tasks with their optimal periods and provides a flexible platform capable of adapting to various project variables and conditions. The practical application of our tool across multiple scenarios illustrates its effectiveness in optimizing project schedules, reducing costs, and mitigating risks. Ultimately, this study contributes to project management by delivering a highly adaptable and powerful decision support system poised to transform how projects are planned, executed, and delivered in an increasingly complex and variable-driven environment.

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