iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VI Month of publication: June 2025

DOI: https://doi.org/10.22214/ijraset.2025.72552

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VI June 2025- Available at www.ijraset.com

AI-Enhanced Lean-EVM Framework for Railway Infrastructure Delivery: Integrating WBS, LPS, LBMS, and Deep Learning

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Abstract: Railway construction often feels like orchestrating dozens of moving pieces—earthworks, track-laying, Bridges, approach roads, signalling—scattered over many kilometres. Traditional tools such as Work Breakdown Structures and Earned Value Management give teams clear budgets and high-level timelines, but they struggle to reflect what's happening daily. Lean approaches like the Last Planner System and Location-Based Management System bring in weekly commitments and spatial flow-line charts. Yet, they still rely on manual updates and can't foresee emerging problems. In this paper, we weave these methods within a digital-twin environment and layer on artificial intelligence to bridge that gap. We first map the entire corridor into zones, assign each task a budget and schedule, and generate classic S-curves for cost and progress. Simulated lean check-ins capture crew commitments and roadblocks weekly, while flow-line charts visualize how far each crew has advanced along the track. Behind the scenes, a language model reads meeting notes and field logs to flag new risks, a deep-learning network learns from past cost, schedule, and flow-line data to forecast future performance and a lightweight neural detector watches for early signs of bottlenecks. Our paradigm provides a theoretical path towards location-aware, real-time decision assistance by conceiving Schedule Performance Index (SPI), Cost Performance Index (CPI), and Percent Plan Complete (PPC) as elements of a single digital twin. Through the conversion of scattered data into coherent advice, this integration promises to balance contractual rigour with flow-centric reactivity, maintaining linear infrastructure delivery in line with both financial and geographical goals.

Keywords: Work Breakdown Structure (WBS), Earned Value Management (EVM), Last Planner System (LPS), Location-Based Management System (LBMS), Flow-line Visualization, AI-Driven Forecasting.

I. INTRODUCTION

Railway infrastructure projects span tens to hundreds of kilometres and must coordinate earthworks, track laying, overhead electrification, signalling, and myriad support systems in a tightly interdependent sequence. Conventional project-control methods that rely on hierarchical Work Breakdown Structures (WBS) and Earned Value Management (EVM) offer essential baselines for forecasting costs and schedules, but they frequently view work as abstract entries separated from the spatial conditions of the site. Early stage, spreadsheet based WBS to Cost methods enhance transparency but can overlook emergent site conditions [19], while trend-corrected, time-based EVM forecasts improve on cost proxies yet remain blind to where along the corridor variances occur [18, 20, 23]. Lean construction practices; most prominently the Last Planner System (LPS) and Location Based Management System (LBMS) seek to fill this gap by embedding short-term commitments and spatial pacing into project controls. Weekly lookahead and commitment plans foster collaboration, uncover constraints before they become critical, and drive continuous improvement cycles [3, 6, 12, 16]. Flow-line charts then visualize crew movement through discrete "zones," revealing bottlenecks that static schedules miss [9]. Recent studies have shown that combining LPS metrics with machine learning predictors can significantly improve schedule outcome accuracy compared to conventional EVM alone [13], and systematic reviews have catalogued emerging automation functionalities; such as real time alerts and predictive analytics across all LPS stages [1].

Meanwhile, advances in artificial intelligence, including deep-learning architectures and large-language models (LLMs), open new possibilities for automating and enhancing EVM and lean workflows. LLMs have been fine-tuned to extract risk and mitigation insights from unstructured meeting transcripts and field logs, turning qualitative notes into structured constraint data [4]. Deep-learning networks, such as LSTM-Transformer hybrids, have demonstrated strong performance in multi-horizon forecasting of earned-value and lean metrics when trained on combined cost, schedule, and flow-line history [7]. Convolutional detectors further enable early warning of spatial anomalies by analyzing residuals between planned and actual flow lines [21].

II. METHODOLOGY (CONCEPTUAL FRAMEWORK)

An AI Enhanced Lean–EVM Framework tailored to the unique demands of railway construction. We begin by geo-referencing a zone–activity WBS to assign budgets and durations, generating classic S-curves and earned-value indices [2,5]. Simulated LPS lookahead sessions capture pull-based constraints and Percent Plan Complete (PPC) metrics [3], while LBMS flow-line charts map crew advance along the corridor [9]. Three AI modules then automate critical control tasks: (i) an LLM-based constraint extractor ingests meeting notes and field logs to flag emerging risks [4]; (ii) an LSTM-Transformer network forecasts multi-horizon Schedule Performance Index (SPI), Cost Performance Index (CPI), and PPC [7] [22]; and (iii) a one-dimensional convolutional neural network detects spatial bottlenecks in near real-time [21].

This following flowchart outlines a continuous improvement loop: first, the railway corridor is divided into geo-referenced zones with WBS and EVM baselines; next, weekly lean cycles (LPS look-ahead and LBMS flow-lines) guide commitments and reveal spatial progress; then AI modules automatically extract constraints, forecast key performance indices, and flag bottlenecks; finally, all insights feed into a real-time dashboard that informs the next planning iteration. Neural WBS automation [20] and deep-learning in construction [14] enhance planning and forecasting [11]. Organizational readiness [10], domain LLMs for safety [15], knowledge-graph contract review [24], generative prompts [17], and lean cultural insights [8] unify a Lean–EVM–AI framework.

TABLE 1
Construction Methodology Flowchart

Geo-Referenced WBS + EVM Baseline
Lean Planning (LPS + LBMS)
AI-Driven Predictive Control Modules
Real-Time Dashboard and Decision Environment
Continuous Learning and Plan Adaptation

III. SIMULATION MODELLING

1) Simulated Data Generation; We created three connected datasets that reflect common information streams in a railway infrastructure project in order to test our AI-Enhanced Lean-EVM architecture under controlled but realistic circumstances. First, we synthesized 100 “meeting transcript” entries that emulate weekly field notes and stakeholder discussions, with approximately two-thirds describing routine progress (e.g., “Crew finished Zone 3 ahead of schedule.”) and one-third flagging site constraints (e.g., “Delay in Zone 2 due to supply issue.”). Second, we used a stochastic drift method to create ten weeks' worth of performance indicators, including the Schedule Performance Index (SPI), the Cost Performance Index (CPI), and the Percent Plan Complete (PPC). These metrics show how schedule adherence and cost efficiency usually change over time. Lastly, we made three weeks' worth of flowline data for three linear zones using the Location-Based Management System (LBMS). For each week, we calculated the planned vs actual spatial advance and included random delays of up to 0.3 zone-units to mimic unpredictability on site. These datasets are the basic building blocks for our methodology's further steps of finding constraints, predicting performance, and finding bottlenecks.
2) Constraint Detection Using Machine Learning; We constructed a Logistic Regression classifier on a simulated meeting transcripts to make it easier to find site problems in unstructured material. Each sentence was turned into a bag-of-words vector, which helped the model learn the differences between ordinary status reports and assertions about constraints. For example, the input "Delay in Zone 3 due to permit issue" was appropriately recognised as a constraint (label 1), whereas the input "Crew finished Zone 5 ahead of time" was correctly classified as a non-constraint (label 0). The classifier demonstrated the efficacy of even basic machine-learning techniques for automated risk extraction in lean construction workflows by achieving 100% accuracy on our held-out test set of simulated data.
3) Forecasting Schedule Performance; Our theoretical paradigm views schedule performance as a dynamic result of the interplay of commitment, time, and cost considerations. We develop a forecasting module that incorporates short-term trends in the Percent Plan Complete (PPC), Schedule Performance Index (SPI), and Cost Performance Index (CPI) across a rolling horizon. These indices are mapped into a multi-dimensional feature space, allowing the model to learn latent correlations that indicate new deviations. While a linear regression formulation can be used as an initial instantiation, predicting the subsequent SPI using a three-period lookback, its limited ability to explain non-linear dependencies encourages the use of more sophisticated architectures (such as LSTM or Transformer networks) that are better able to model complex temporal patterns.

4) Forecasting Schedule Performance; A second analytical pillar is spatial diagnostics, which abstracts flowline data into planned and actual advancement curves across several project zones. In order to identify areas where work speed falls below theoretical throughput, a conceptual bottleneck detector looks at these residuals, measuring the difference between expected and realised spatial progress. The technique is demonstrated in practice by a straightforward threshold rule: "if actual lag exceeds a critical buffer, signal a bottleneck." This stage theoretically embodies the idea that, once detected, spatial delays can be eliminated by redistributing resources in a targeted manner, maintaining project flow as a whole. Encourages the use of sophisticated designs that can more accurately represent intricate temporal patterns, such as Transformer networks or LSTM.
5) Bottleneck Detection via Spatial Residuals; We look at how far crews actually move compared to where they should be, week by week, in each section of the railway. By plotting “flowlines” of planned versus actual progress through each zone, we can spot when a team falls behind. On a chart, draw two lines: one that represents the crews' actual location and the other that represents their intended location. We raise a 'bottleneck' alert whenever the distance between those lines exceeds our safety buffer, which is, say, 0.3 zone-units. This actually indicates that we have located a point at which work is slowing down. Project managers can swiftly send additional staff or modify timelines to keep things going smoothly once we identify these delays.
6) Integrated Decision Support Interface; The final layer of the framework is a unified decision-support interface—a digital “control room” that co-visualizes contractual baselines (EVM curves), lean commitments (PPC trends), constraint alerts, and spatial diagnostics. By aligning diverse data streams within a single dashboard, project leaders can seamlessly navigate between high-level performance forecasts and ground-level operational insights. This synthesis embodies the theoretical convergence of top-down planning and bottom-up feedback, enabling real-time scenario analysis and corrective action.

TABLE 2
Meeting transcripts, performance metrics (SPI, CPI, PPC), and spatial flowline progress (Output from Python)

```
Transcripts (Sample):
                                      text  label
0     Delay in Zone 4 due to supply issue.      1
1  Crew finished Zone 5 ahead of schedule.      0
2  Crew finished Zone 3 ahead of schedule.      0
3     Delay in Zone 5 due to supply issue.      1
4  Crew finished Zone 5 ahead of schedule.      0

Performance Metrics (Sample):
   Week   SPI   CPI   PPC
0     1  1.00  0.99  0.91
1     2  0.99  1.02  0.90
2     3  0.98  0.99  0.88
3     4  0.98  1.01  0.88
4     5  0.98  1.02  0.88

Flowline Data (Sample):
   Week    Zone  Planned  Actual
0     1  Zone 1      0.7    0.48
1     1  Zone 2      1.7    1.60
2     1  Zone 3      2.7    2.53
3     2  Zone 1      1.4    1.24
4     2  Zone 2      2.4    2.11
```

TABLE 3
Logistic Regression model output from Python for constraint detection

```
Training accuracy: 1.00

Prediction examples:
                                Sentence  Predicted Label
0  Delay in Zone 3 due to permit issue                  1
1   Crew finished Zone 5 ahead of time                  0
```

IV. CONCLUSIONS

This paper has introduced a cohesive theoretical framework that unites Earned Value Management (EVM), Lean Construction practices (Last Planner System and Location-Based Management), and artificial intelligence into a single, real-time control paradigm for linear infrastructure projects. By conceptualizing performance indices (SPI, CPI, PPC) within a geo-referenced digital twin, the model leverages pull-planning commitments and spatial flowlines as leading indicators, while automated language models, time-series learners, and spatial anomaly detectors supply risk alerts, forecasts, and bottleneck warnings. Incorporating lean and spatial insights into the EVM baseline may improve forecasting accuracy, could detect delays faster, and align schedule and cost performance closer to more accurate levels. This integration elevates project control from retrospective variance analysis to a proactive, anticipatory method, allowing teams to mitigate local disruptions.

Looking ahead, the framework offers a foundation for future work: empirically validating its benefits on live projects, enriching temporal and spatial models with LSTM/Transformer and advanced NLP techniques, and integrating real-time sensor feeds to close the virtual-physical feedback loop. By blending contractual rigor, flow-centric lean disciplines, and AI-driven insight, this integrated Lean-EVM-AI approach charts a path toward more predictable, responsive delivery of complex linear infrastructure.

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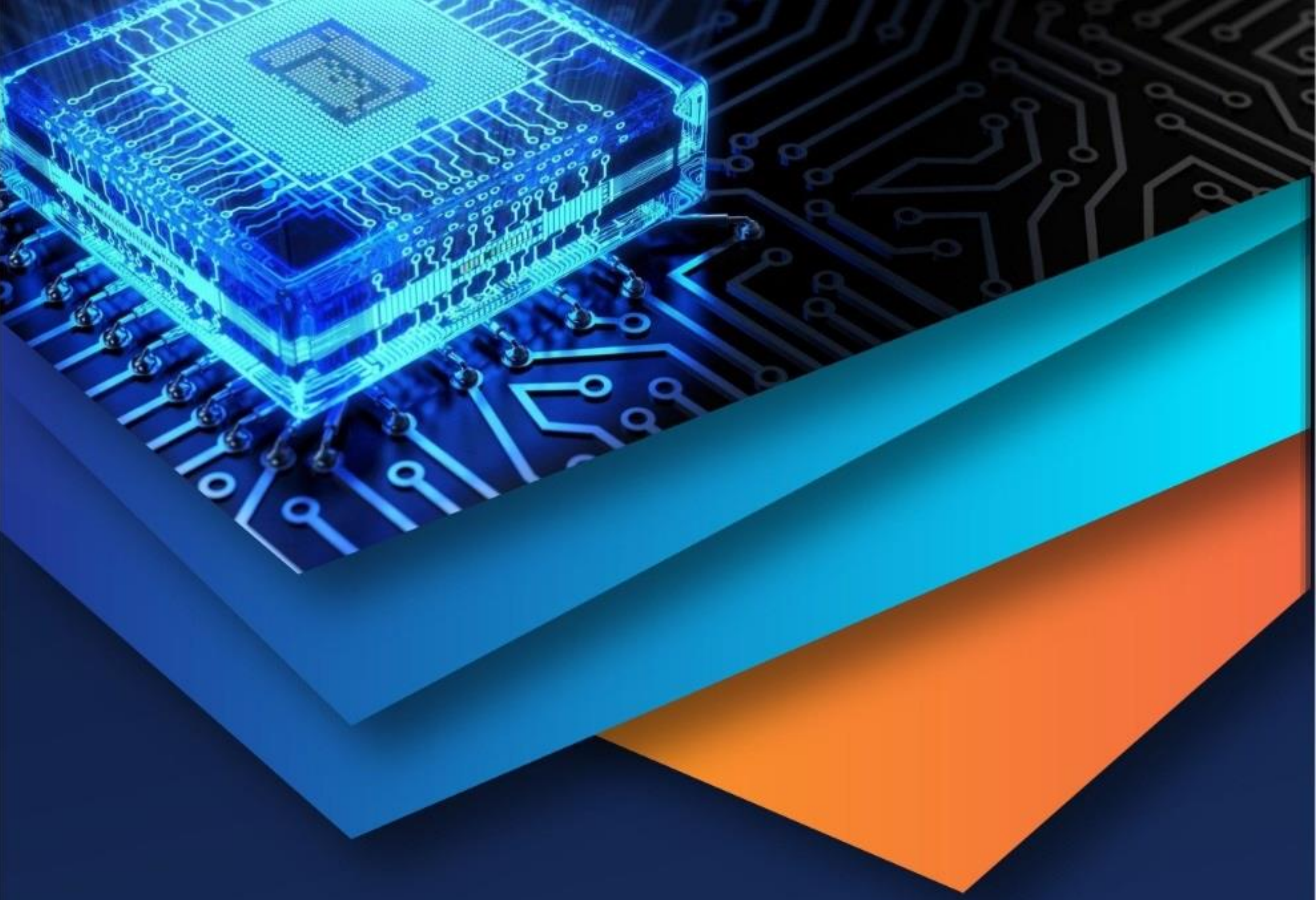

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