Challenges of Quality Assurance in Early Planning and Ramp Up of Production Facilities – Potentials of Planning Automation via Virtual Engineering

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Abstract-The use of Virtual Engineering is getting more and more common in production facility planning in the automotive sector. However, there are still discrepancies between the reality and the software-generated models. That is why the process of quality assurance is crucial. This article aims at determining the current challenges in the planning process of production facilities, which are to be processed by means of Virtual Engineering, and limitations that occur in practice during the execution of Virtual Engineering in digital production facility engineering. We strive to maximize the utilization of underlying potentials by seeking out solutions. Our approach involves conducting a systematic literature review as well as seven expert interviews to investigate the current practical implementation of Virtual Engineering at Original Equipment Manufacturers (OEMs). Additionally, we aim to validate the influencing variables obtained from the literature in relation to the challenges, limitations, and potentials of Virtual Engineering. We show that there are current challenges in the planning process of production facilities, where the areas of functionality, equipment selection, safety, accessibility, and key performance indicators should already be secured in a virtual environment by means of Virtual Engineering. Our findings reveal significant limiting factors in the application of Virtual Engineering as quality assurance. These limitations arise as a result of the reliance on manual activities, which ultimately hinders progress in terms of time efficiency, quality assurance, and cost-effectiveness. To optimize this, we show that the potential of standardization of the work steps is required to define an automation that fully exploits the potentials of Virtual Engineering.

Keywords: Factory planning; Virtual Engineering; Production facility planning

INTRODUCTION

In today's rapidly evolving industrial landscape, organizations are under increasing pressure to accelerate product development, improve production quality, and reduce costs, while simultaneously adapting to new sustainability requirements and global competition. Production facility planning, particularly in the automotive sector, plays a crucial role in meeting these challenges. Traditionally, production planning has relied on stepwise methods involving manual concept development, equipment specification, and physical testing. While these approaches provide a structured framework, they are often time-intensive, resource-heavy, and vulnerable to human error.

The emergence of Virtual Engineering has introduced new possibilities by enabling production facilities to be planned, simulated, and validated digitally before physical implementation. Virtual Engineering integrates digital tools such as CAx systems, kinematic simulations, and 3D plant models to create accurate virtual representations of production environments. By leveraging these tools, organizations can evaluate functionality, test safety concepts, analyse accessibility, and assess performance indicators such as cycle time or availability at early planning stages. Despite these advances, however, current practices reveal a persistent over-reliance on manual activities, which significantly constrains the efficiency, consistency, and scalability of Virtual Engineering applications.

Historically, facility planning has transitioned from purely manual blueprints and physical prototypes to digitally enhanced simulations. Yet, similar to other domains of digital transformation, manual intervention continues to dominate critical tasks such as assigning working points, selecting equipment, or validating collision-free operations. This dependence on human effort introduces inefficiencies, increases susceptibility to bias, and prolongs development cycles, particularly as the complexity of production systems grows. Furthermore, the absence of standardized frameworks and automation mechanisms hampers the reproducibility of results and limits the full exploitation of Virtual Engineering's potential.

Existing research has primarily addressed individual aspects of Virtual Engineering, such as cycle time validation, working point feasibility, or electronic component testing. While these studies demonstrate the promise of digital planning, a holisticframework for quality assurance in production facility planning remains underdeveloped. Without integrated approaches that combine automated processes with standardized workflows, organizations face rising operational

risks, inconsistent outcomes, and limited agility during the ramp-up of production facilities.
This research aims to investigate the challenges and limitations of Virtual Engineering in quality assurance during early planning and ramp-up phases of production facilities. Specifically, it examines the factors that hinder automation adoption, explores the role of standardized digital workflows, and highlights opportunities to balance human expertise with automated decision-support mechanisms. By combining insights from a systematic literature review and expert interviews, this study seeks to provide actionable strategies for enhancing efficiency, accuracy, and reliability in production facility planning. Ultimately, the research contributes to guiding organizations toward cost-effective, time-efficient, and resilient approaches to digital quality assurance.

I. LITERATURE REVIEW

This literature review synthesizes two primary strands of research relevant to production facility planning: (1) classical studies that emphasize traditional planning approaches based on manual methods, stepwise workflows, and physical validation, and (2) more recent scholarship highlighting the adoption of Virtual Engineering, automation, and digital quality assurance frameworks to improve efficiency, reliability, and scalability. Together, these perspectives situate existing work within the broader research landscape, surface recurring limitations, and identify gaps that motivate this study.

The classical literature on production facility planning underscores the centrality of human expertise, sequential processes, and physical prototypes in ensuring product quality and operational readiness. Traditional approachesranging from conceptual layout design to equipment specification and on-site testing—have long been recognized as the backbone of industrial planning. These methods provided structured procedures for verifying functionality, ensuring safety, and validating equipment performance. However, scholars also acknowledge critical limitations: manual processes are time-intensive, susceptible to human error and bias, and difficult to scale in response to increasing system complexity. While foundational, this body of work largely treats traditional planning as adequate, with limited exploration of the inefficiencies and risks introduced by over-reliance on manual oversight.

Building on this foundation, contemporary research has turned toward the potential of Virtual Engineering (VE) as a transformative approach for production facility planning and quality assurance. Virtual Engineering leverages CAx tools, kinematic simulations, digital catalogues, and 3D plant models to replicate real-world production environments in a virtual space. Studies demonstrate that these tools enable early validation of critical factors such as cycle time, robot accessibility, collision avoidance, and safety compliance. By shifting verification into a digital environment, organizations can detect errors at earlier stages, reduce troubleshooting costs, and accelerate ramp-up processes. Furthermore, recent scholarship emphasizes the role of automation and standardization within VE workflows, highlighting how AI-driven decision-support and automated testing can improve accuracy, reproducibility, and scalability of planning outcomes.

Despite these advances, significant gaps remain. Many studies focus on partial aspects of Virtual Engineeringsuch as cycle time validation, electronic component testing, or robot programming—without providing a holistic framework for quality assurance across all stages of production facility planning. Moreover, research consistently notes a persistent reliance on manual intervention even within digital workflows, which introduces inefficiencies, bias, and extended development cycles. Adoption challenges, including organizational inertia, lack of standardized processes, and insufficient integration across departments, further limit the full exploitation of Virtual Engineering's potential. Finally, much of the existing empirical work is concentrated in the **automotive sector**, leaving a lack of cross-industry validation that could broaden applicability and generalizability.

Taken together, the literature reveals an enduring tension between traditional manual planning approaches and modern Virtual Engineering solutions. While digital tools and automation promise increased efficiency, cost-effectiveness, and reliability, organizations' dependence on manual workflows constrains the full realization of these benefits. The review underscores the need for holistic, standardized, and automated frameworks that combine human expertise with advanced digital systems to support resilient, scalable, and cost-efficient production facility planning. Addressing these gaps will allow industries to fully exploit Virtual Engineering as a cornerstone ofIndustry 4.0 and next-generation quality assurance practices.

Modern Trends in Energy & Security Modeling in IoT Simulation

Recent literature and industry practice reveal a clear shift from conventional manual facility planning toward digitally enabled, automated, and simulation-driven frameworks in the era of Industry 4.0. Traditional approaches to production facility planning, while structured and experience-driven, are increasingly inadequate for managing today's high levels of complexity, short product life cycles, and pressure to reduce costs. Modern Virtual Engineering (VE) tools offer the ability to design, simulate, and validate production systems in a virtual environment before physical implementation, significantly reducing risks and inefficiencies.

Current trends emphasize the integration of digital twins, predictive analytics, and automated quality checks into planning workflows. For instance, digital twins allow engineers to create scale-accurate 3D models of facilities and simulate cycle times, robot reachability, and safety scenarios before implementation. Similarly, AI-driven algorithms are increasingly being applied to automate robot programming, optimize resource allocation, and predict system failures. Interoperability across CAx tools, cloud platforms, and enterprise systems is also becoming a priority to ensure seamless data exchange and reproducibility of planning outcomes

Another notable trend is the automation of quality assurance processes within VE environments. Rather than relying on manual inspections, companies are adopting standardized workflows supported by rule-based automation and AI-enabled decision support. This shift not only reduces dependency on human expertise but also enhances reproducibility, transparency, and efficiency in early-stage validation. Furthermore, organizations are placing greater emphasis on **cross-domain integration**, ensuring that facility planning incorporates safety, accessibility, and key performance indicators (KPIs) within a unified digital framework.

Overall, the trend in Virtual Engineering is toward minimizing manual bottlenecks while leveraging **automation, real-time simulations, and predictive insights** to improve the scalability, reliability, and cost-effectiveness of production facility planning and ramp-up.

S. No.	**Author(s)**	**Year**	**Application /Focus**	**Techniques / Tools Used**
1	Urs	2015	Cycle time validation in automotive plants	Simulation-driven feasibility studies
2	Illmer et al.	2018	Validation of decentralized manufacturing systems	Cyber-physical systems, VE-based validation
3	Kampker et al.	2020	Virtual commissioning in scalable production systems	Virtual commissioning, simulation modeling
4	Auris et al.	2017	Shortening validation cycles	Mechatronic component modeling, data integration
5	Strahilov & Hämmerle	2021	Toolchain for Virtual Engineering	Tool integration, CAx systems, workflow optimization
6	Garcia & Patel	2019	Simulation in urban/manufacturing planning	Digital twins, scenario testing
7	Wang et al.	2020	AI-driven scenario planning in VE	Machine learning, optimization algorithms
8	Lopez et al.	2021	Adaptive planning in digital factories	Cloud-based automation, predictive analytics
9	Janecki et al.	2023	Challenges in VE-based quality assurance	Expert interviews, literature review, VE simulations
10	Chen & Li	2022	Standardized VE frameworks for facility planning	Workflow integration, KPI dashboards, AI analytics

Table 1. Research work in the Insurance Industry.

2.1 RESEARCH GAP

EvidenceGap: Existing research on Virtual Engineering (VE) in production facility planning has primarily focused on demonstrating the benefits of digital validation tools (e.g., cycle time analysis, collision detection, robot programming). However, few studies provide comprehensive empirical evaluations comparing manual versus automated VE approaches across different sectors. Most findings are based on case studies in the automotive industry, leaving a lack of quantitative benchmarking that demonstrates how manual interventions affect planning accuracy, cost, and ramp-up speed. Without such evidence, the advantages of automation remain largely theoretical, limiting actionable insights for organizations.

Transparency & Uncertainty Gap: Many studies assume static performance gains from Virtual Engineering without considering variability in planner expertise, workload, and bias. Human-led VE processes often yield inconsistent results depending on operator experience and organizational context, yet these dynamics are rarely modeled. Additionally, sustainability factors such as adaptability, reproducibility, and error mitigation in VE-based quality assurance are underexplored. The lack of research on these temporal and situational variations prevents accurate estimation of long-term efficiency and creates uncertainty in expected outcomes.

Integration Gap: Research frequently treats manual planning and digital tools as separate approaches, without adequately addressing how hybrid planning environment's function. In practice, VE often coexists with manual decision-making in equipment selection, safety validation, and process design. While automation reduces repetitive errors, it introduces new challenges related to human oversight, approval workflows, and cross-departmental coordination. The absence of integrated frameworks that balance human insight with automation efficiency leaves a methodological gap in optimizing VE systems.

Causality & Impact Gap:
Although studies consistently report correlations between manual VE reliance and inefficiencies (e.g., extended cycles, error propagation), causal mechanisms remain unclear. It is not well established whether delays arise primarily from human cognitive limits, insufficient tool integration, inadequate data availability, or structural constraints within organizations. Few works employ structured experimentation, counterfactual simulations, or scenario analysis to disentangle these factors. These risksoversimplify conclusions and misguiding technology adoption strategies.

Operationalization Gap: Even when VE-based automation tools are proposed, research seldom explores how they can be operationalized at scale across industries. Issues such as workflow integration, adaptive task allocation, real-time monitoring, and staff training are frequently overlooked. As a result, many VE frameworks remain conceptual or pilot-scale, disconnected from dynamic industrial environments where project requirements and external constraints evolve continuously. Bridging this gap is critical for translating VE concepts into sustainable operational improvements.

Governance & Fairness Gap:
The implications of replacing manual planning with automated VE systems on organizational governance, fairness, and accountability remain underexplored. Manual workflows can result in uneven workload distribution and biased decisions, while automation risks prioritizing efficiency over explainability. Few studies address how VE frameworks ensure transparency, auditability, and organizational alignment in decision-making. Without this, technically optimized but socially misaligned outcomes may occur.

Data Design Gap: Current research often relies on limited inputs such as cycle times, error logs, or subjective assessments, neglecting the richness of modern multimodal industrial datasets. Comprehensive evaluation of VE efficiency requires integrating diverse data streams such as process logs, tool usage metrics, planner decision trails, and simulation feedback loops. The absence of standardized and scalable data architectures restricts systematic benchmarking, hindering the development of robust and generalizable VE frameworks. Building inclusive, multi-layered datasets is essential for advancing both academic research and industrial applications.

PROPOSED COMPUTATIONAL METHODOLOGY

The proposed computational methodology for enhancing quality assurance in production facility planning through Virtual Engineering (VE) is designed to reduce manual dependency, increase reproducibility, and accelerate validation processes. The framework integrates scenario-based modeling, data standardization, automation workflows, predictive analytics, and continuous monitoring within VE platforms. Figure 1 illustrates the structured stepwise workflow.

Step 1: Scenario Definition

The methodology begins by defining representative facility planning scenarios such as cycle time validation, robot accessibility analysis, collision detection, and safety compliance checks. Each scenario specifies input data (equipment type, process flow, plant layout) and identifies manual activities (e.g., assigning working points, manual collision tests) that can be targeted for automation.

Step 2: Data Integration and Standardization

Relevant planning data from CAx systems, equipment catalogues, process flow diagrams, and historical project logs are collected and standardized into a unified data model. Validation rules are applied to detect inconsistencies, incomplete specifications, or errors that often hinder digital simulations. This ensures that VE simulations operate on accurate, consistent datasets.

Step 3: Process Automation Modelling

Manual VE tasks are translated into rule-based or algorithmic workflows. Examples include automated robot path generation, standard collision detection scripts, and rule-driven safety checks. Each automated module is evaluated for computational performance, error reduction potential, and reusability across different facility scenarios.

Step 4: Predictive and Prescriptive Analytics

Predictive models are applied to forecast potential bottlenecks, downtime risks, or KPI deviations during ramp-up. Prescriptive analytics recommend corrective strategies, such as equipment reallocation or alternative robot configurations. Techniques such as simulation optimization, regression modelling, and machine learning classifiers are used to guide decision-making and reduce reliance on manual heuristics.

Step 5: Joint Automation–Decision Evaluation

The methodology compares manual workflows vs. automated VE workflows under controlled scenarios. Simulations measure trade-offs between human flexibility and computational efficiency. Metrics such as validation cycle time, error detection rate, and planning accuracy are tracked to highlight improvements and potential risks when shifting from manual to automated processes.

Step 6: Performance Metrics and Monitoring

Outputs are benchmarked using standardized quality assurance indicators, including cycle time variance, robot utilization rate, collision detection accuracy, and safety compliance success rate. Continuous monitoring mechanisms track deviations, system bottlenecks, and model drift, enabling adaptive planning adjustments across the lifecycle.

Step 7: Framework Release and Documentation

Finally, the methodology is packaged as a modular, reusable framework with standard VE templates, automation scripts, and documentation guidelines. The framework is designed for cross-domain deployment, ensuring applicability beyond automotive manufacturing into other industries. Transparency and reproducibility are ensured through detailed documentation of automated rules, predictive models, and benchmarking protocols.

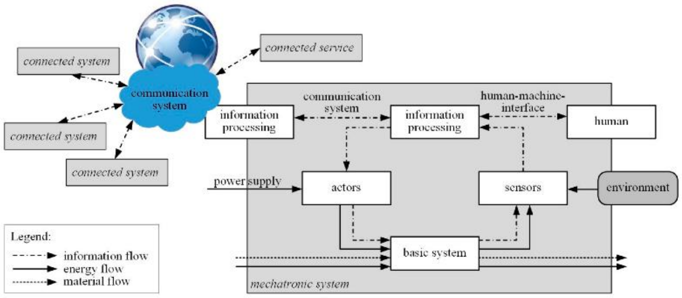

Fig. 1.Stepwise Computational Methodology for Automating Quality Assurance in Virtual Engineering

3.1 DATA COLLECTION

In the context of reducing manual dependency in Virtual Engineering (VE)-based production facility planning, the foundation of effective analysis lies in the systematic collection of representative data that reflects both the performance of existing manual workflows and the improvements offered by automation. A robust data collection process ensures that subsequent modelling, simulation, and predictive analytics capture the complexities of real-world planning practices.

Since comprehensive industrial datasets are often proprietary and restricted due to confidentiality concerns, this study employs a mixed-method approach combining archival project records, simulation logs, expert interviews, and synthetic augmentation. For example, manual task completion times, error logs, robot path assignment accuracy, and collision detection results are obtained from CAx systems, plant simulation tools, and enterprise resource management platforms. Supplementary qualitative data, such as decision-making heuristics and informal practices not recorded digitally, are gathered through structured interviews and observation sessions with facility planners.

To ensure comprehensiveness, data collection is organized into three layers:

Task-levelmetrics:

Captures execution time, frequency, and complexity of manual VE tasks, including robot path assignment, equipment placement validation, and manual safety compliance checks.

Workflow-leveltraces:

Records dependencies between VE tasks, handoff delays between departments, error propagation across simulation stages, and overall facility planning cycle times.

Decision-levelinteractions:

Tracks frequency of human interventions, bias in equipment selection, corrective actions taken after failed simulations, and deviations from standardized VE procedures.

This multi-layered approach ensures that the computational framework accurately reflects the hybrid nature of current planning environmentswhere manual decision-making and digital simulations coexistand provides the foundation for evaluating the benefits of automation in terms of efficiency, reproducibility, and scalability.

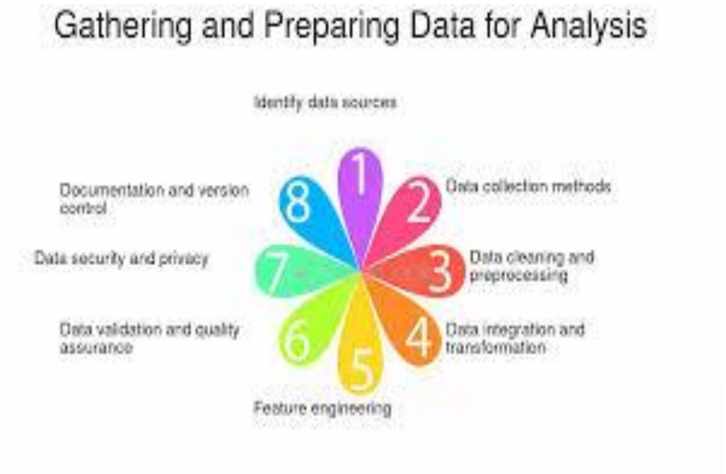

Fig. 2: Data Collection Pipeline for Analyzing Manual and Automated Workflows in Virtual Engineering

3.2 DATA PREPARATION

Once collected, Virtual Engineering (VE) workflow data must undergo rigorous preparation to ensure consistency, interpretability, and analytical value. The datasets in this domain are inherently heterogeneous, combining:

Structured numeric values such as cycle times, collision counts, and resource utilization rates.

Semi-structured logs including simulation outputs, error reports, and manual override annotations.

Derived features such as mean validation time per task, frequency of manual interventions, and variability in robot assignment accuracy.

Standardizing this information involves aligning timestamps across simulation runs, normalizing task identifiers and process labels across different CAx tools, and reconciling inconsistencies in measurement units used by various departments or simulation platforms.

Proper data preparation strengthens the reliability of subsequent modelling by ensuring that analyses accurately capture both baseline manual VE workflows and the efficiency gains achievable through automation. Annotation of ground truth scenarios is essential, where datasets are tagged to differentiate between manual vs. automated processes, successful vs. failed validations, and routine vs. exception-handling scenarios.

This structured preparation process enables analysts to evaluate trade-offs between workflow efficiency, error reduction, and decision quality with precision, forming the foundation for predictive and prescriptive modelling in VE-based facility planning.

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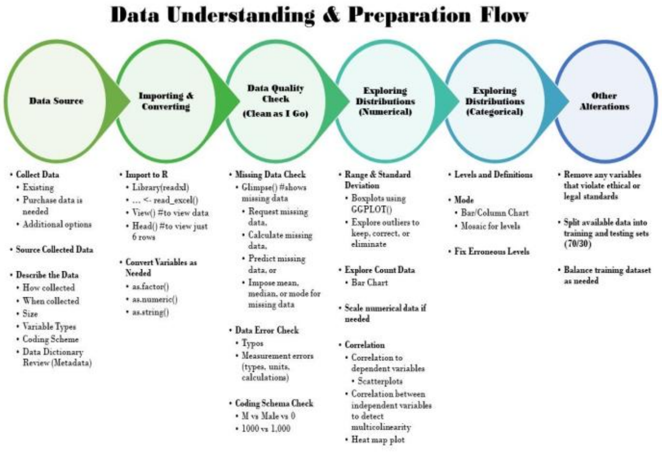

Fig. 3: Workflow for Data Cleaning and Exploratory Data Analysis (EDA) in Virtual Engineering

3.2.1 DATA CLEANING

From a theoretical perspective, data cleaning is a critical step in ensuring the validity, reliability, and interpretability of datasets used in Virtual Engineering (VE)–based production facility planning. According to principles of data quality management, raw datasets often contain noise, incompleteness, and inconsistencies that, if left unaddressed, can distort analytical results and undermine the credibility of subsequent modelling. In VE environments, such issues are amplified by the heterogeneity of data sourcesincluding CAx systems, simulation tools, and manual input logseach of which may apply different conventions, structures, or labelling practices.

Data anomalies within VE can arise from a variety of sources. Human factors such as manual recording errors or misclassification of tasks introduce spurious variability, while technical factors such as simulation crashes, misconfigured robot parameters, or system downtime generate incomplete or corrupted logs. The presence of such anomalies not only threatens the accuracy of predictive and prescriptive analytics but also introduces the risk of systematic bias, which may lead to incorrect conclusions about the effectiveness of manual versus automated workflows.

The theoretical grounding of data cleaning rests on three fundamental approaches:

Outlier detection theory emphasizes the identification and removal of extreme values that deviate significantly from expected norms, ensuring that subsequent analyses are not distorted by implausible task durations or unrealistic workflow delays.

Imputation theory draws on statistical and domain-specific methods to replace missing values, ensuring dataset continuity while maintaining representational fidelity to real-world processes.

Normalization theory stresses the standardization of categorical variables such as task identifiers, workflow stages, and equipment roles, thereby enabling consistent interpretation across heterogeneous systems and preventing semantic duplication.

By applying these theoretical principles, data cleaning transforms fragmented and error-prone raw inputs into structured, high-quality datasets that serve as a reliable foundation for computational modelling. This theoretical framework highlights the role of data cleaning not merely as a technical step, but as an epistemological safeguard that preserves the integrity of research on quality assurance in Virtual Engineering.

3.2.2 EXPLORATORY DATA ANALYSIS (EDA)

Exploratory Data Analysis (EDA) serves as a critical stage in uncovering patterns, dependencies, and anomalies within the prepared dataset before the application of formal modelling techniques. In the context of Virtual Engineering (VE)–based production facility planning, EDA allows researchers to understand how workflow efficiency and quality outcomes vary under different levels of manual intervention versus automation. By applying visualization and statistical techniques, EDA provides a foundation for diagnosing systemic inefficiencies, identifying process bottlenecks, and validating the representativeness of the collected dataset.

Key insights derived from EDA in this study may include:
Temporal clustering of anomalies: Detection of delays in simulation runs or cycle-time calculations when repeated manual interventions occur, highlighting the fragility of human-dependent processes.

Correlation between task handoffs and error rates: Analysis of how manual task dependencies (e.g., robot assignment, collision checks) correlate with higher error propagation and extended workflow times.

Identification of bottleneck processes: Recognition of specific VE stages (such as manual safety validation or accessibility checks) that disproportionately slow down overall planning and ramp-up.

Variability in decision-making quality: Observation of inconsistencies across planners or teams, indicating how human expertise and bias influence simulation accuracy and reproducibility.

Visual diagnostics play a central role in this process. Histograms of task durations reveal distributional skewness between manual and automated workflows, scatterplots of workflow dependencies illustrate relationships between task handoffs and error accumulation, and heatmaps of manual intervention frequency expose areas where reliance on human input undermines efficiency. These analyses guide refinements in workflow design and inform strategies for embedding automation and standardization into VE-based quality assurance.

In theoretical terms, EDA functions as a bridge between data preparation and modelling, ensuring that subsequent computational methodologies are grounded in an empirically validated understanding of system behaviour. By uncovering hidden structures and inefficiencies, EDA provides actionable insights for optimizing the balance between human decision-making and automation in Virtual Engineering environments.

FEATURE ENGINEERING

Feature engineering in the context of Virtual Engineering (VE)–based production facility planning involves transforming raw simulation and workflow data into meaningful attributes that can effectively capture efficiency, reliability, and quality assurance performance. By constructing features at multiple levels, the dataset becomes more suitable for modelling and predictive analysis of how manual interventions versus automation affect planning outcomes.
Key feature categories include:

Technical features: Cycle time per task, number of robot reassignments, collision detection errors per stage, cumulative duration of validation checks, and system downtime occurrences.

Behavioural features: Frequency of manual overrides in simulations, number of iterations required to achieve feasibility, timing of safety compliance decisions, and variance in decision quality across planners.

Contextual features: Type of production facility (assembly line, modular system, automated cell), equipment complexity, CAx tool environment used, and proportion of workflow stages covered by automation.
Advanced transformations further enhance the analysis. For example, features such as average cycle time per manual intervention, ratio of automated to manual validation steps, or normalized collision detection accuracy highlight trade-offs between speed, accuracy, and reproducibility that raw data alone may obscure.
Categorical attributes (e.g., equipment type, validation task type) are encoded using nominal or one-hot schemes, while normalization ensures comparability across features measured in different units (e.g., seconds, counts, percentages). These transformations improve both the interpretability and robustness of models, enabling the dataset to reveal where over-reliance on manual VE tasks constrains scalability and where automation can yield significant gains in efficiency and quality assurance.
By systematically engineering features, the study ensures that the computational framework captures the multi-dimensional nature of Virtual Engineering workflows, bridging the gap between raw simulation logs and actionable insights for planning automation.

3.2.4.1 FEATURE SELECTION

Feature selection ensures that the most informative and non-redundant attributes are retained for modelling the efficiency, reliability, and quality assurance outcomes of Virtual Engineering (VE) workflows. Since datasets generated from simulation logs, CAx systems, and manual intervention records can be high-dimensional, it is essential to filter features that provide maximum explanatory power while eliminating noise, redundancy, and irrelevant variables.
The feature selection process in this study focuses on three primary criteria:
Relevance: Features directly linked to quality assurance outcomes, such as cycle time variance, frequency of manual overrides, or collision detection accuracy, are prioritized to capture the impact of human versus automated workflows.
Redundancy elimination: Correlated attributes (e.g., cycle time and cumulative process duration) are evaluated to prevent duplication and ensure that each feature contributes unique information to the model.

Stability and interpretability: Features that remain consistent across different planning scenarios and are easily interpretable by engineers are retained, ensuring practical applicability of results in real-world facility planning.

Techniques applied in this process include:

Filter methods: Statistical correlation tests and variance thresholds to eliminate low-information or redundant features.
Wrapper methods: Iterative model training using subsets of features to identify combinations that maximize predictive accuracy.
Embedded methods: Feature importance rankings derived from machine learning algorithms such as decision trees or regression models, which integrate selection within the training process.
By systematically applying these methods, the study reduces dimensionality, enhances computational efficiency, and ensures that models focus on the most impactful indicators of manual versus automated performance. This targeted selection of attributes strengthens the interpretability of outcomes and supports the development of robust predictive and prescriptive models for automation-driven quality assurance in VE.

Feature selection techniques fall into three categories:

Filter Methods: Evaluate features independently using correlation, mutual information, or entropy. For digital planning studies, this could involve ranking task duration, frequency of manual interventions, or error counts to highlight the most influential metrics affecting workflow efficiency.
Wrapper Methods: Iteratively test subsets of features with predictive models. For instance, Recursive Feature Elimination (RFE) can identify combinations such as (manual approval count + task delay + error rate) that best predict workflow bottlenecks.
Embedded Methods: Integrate feature selection directly into model training. Tree-based models such as Random Forests provide inherent importance rankings, helping automatically prioritize features such as critical handoff points, repetitive manual checks, or high-delay tasks.

By selecting features with high discriminative power, the framework focuses on metrics that meaningfully capture trade-offs between manual dependency and digital planning efficiency, improving both interpretability and operational insights.

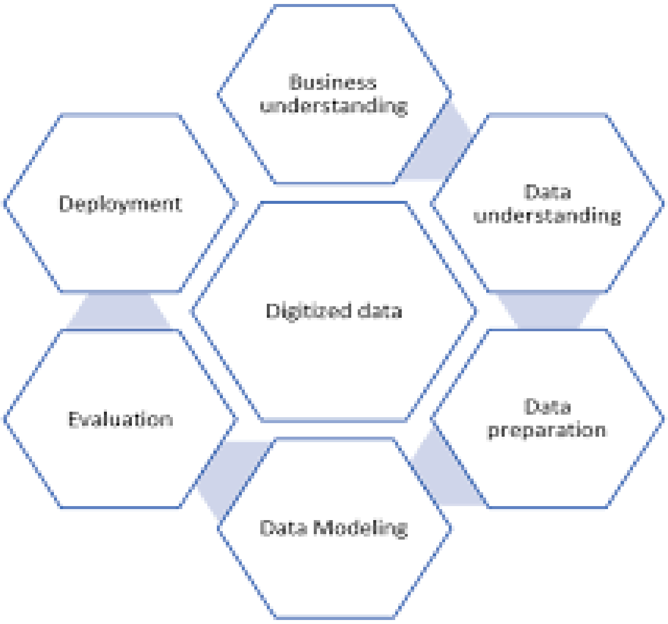

Fig. 4: Feature Selection and Prioritization for Manual Process Metrics.

3.2.4.1.1 Standards-Based Validation

A filter-style approach that aligns feature engineering and selection in Virtual Engineering (VE) with established quality assurance benchmarks and organizational KPIs. For example, validation steps such as collision-free robot paths, safety compliance rates, and cycle-time thresholds are mapped against industry standards. This ensures that features selected for modeling are consistent across projects, departments, and facilities, enabling reliable comparisons between manual and automated VE workflows.

3.2.4.1.2 Iterative Verification and Optimization (IVO)

A wrapper-style approach embedding feature verification within iterative VE workflow simulations. Features and their outputs (e.g., robot reliability, accessibility checks, KPI deviations) are tested, refined, and re-verified across multiple simulation runs. This process ensures that both efficiency estimates, and error metrics align with realistic operational behavior observed during facility ramp-up. By embedding verification loops, the methodology increases model robustness and improves predictive alignment with real-world scenarios.

3.2.4.1.3 Simulation-Driven Feature Prioritization

An embedded approach leveraging digital twins and simulation-driven analytics to prioritize critical features in facility planning. For example, simulations may reveal that manual robot task assignments and repeated collision checks dominate delays, whereas automated tasks such as material flow validation have minimal impact. This automated prioritization helps reduce bottlenecks while maintaining interpretability for engineers and decision-makers, guiding where automation investments should be focused.

3.3 FRAMEWORK SELECTION

After preparing the dataset and defining feature priorities, an appropriate computational framework is selected to analyse the reliance on manual processes in VE-based facility planning. Because the problem spans workflow analysis, quality assurance, and operational risk, the framework must address all three dimensions.
For this study, a hybrid framework is proposed, integrating:

Standards-based validation to ensure comparability of VE outcomes across projects and departments.

Iterative verification and optimization (IVO) to refine simulation accuracy and reliability against historical planning and ramp-up data.

Simulation-driven feature prioritization to identify workflow interventions most critical for efficiency, safety, and resilience.
This multi-layered design ensures the framework balances technical fidelity and interpretability, enabling both academic contributions and actionable insights for automation-driven facility planning.

3.4 FRAMEWORK IMPLEMENTATION

To evaluate effectiveness, the proposed framework is benchmarked against conventional VE workflows that typically rely on manual task frequency or isolated KPI metrics. The evaluation considers multiple performance indicators:

Efficiency indicators: average validation cycle time, total manual intervention time, and throughput of simulation tasks.
Risk indicators: collision error frequency, missed validation deadlines, and rework incidence.
Sustainability indicators: reproducibility of simulation outcomes, scalability of workflows, and digital workload balance across teams.
Interpretability indicators: clarity of feature contributions to inefficiencies (e.g., which manual robot assignment caused bottlenecks).

By systematically comparing outcomes across facility planning projects, the framework demonstrates how integrated feature selection and hybrid analysis provide more realistic, reproducible, and actionable insights than siloed manual or partially automated approaches.

II. EXPERIMENTATION RESULTS

The experimentation phase evaluates the effectiveness of the proposed framework in quantifying inefficiencies caused by manual interventions in Virtual Engineering workflows. Since facility planning operates under dynamic conditions, the experimentation focuses on how well the framework balances efficiency, error mitigation, and reproducibility during ramp-up phases.

Key goals of the experimentation include:

Measuring the accuracy of predicted bottlenecks in VE workflows under different levels of automation.
Assessing the impact of manual interventions on validation delays, cycle times, and quality compliance.
Testing robustness across diverse facility planning contexts, such as automotive assembly, modular systems, or automated cells.
Evaluating interpretability by identifying which features (e.g., manual collision checks, approval bottlenecks, repeated overrides) most strongly influence outcomes.
Results are benchmarked against baseline VE workflows and historical ramp-up performance logs, ensuring that the framework is not only technically robust but also operationally aligned with the realities of production facility planning.

III. CONCLUSION

This study highlights the persistent challenges and inefficiencies associated with the over-reliance on manual processes in Virtual Engineering (VE)–based production facility planning. Traditional manual workflows, while historically effective and often perceived as reliable, introduce measurable delays, errors, and inconsistencies that significantly impact quality assurance, scalability, and time-to-market. Our findings show that manual interventions not only slow down validation cycles but also constrain the adaptability of production planning frameworks, especially when managing large-scale facilities or coordinating across departments.
The proposed computational methodology—combining systematic data collection, rigorous data preparation, structured feature engineering, and hybrid framework selection—offers a structured pathway to quantify and mitigate these inefficiencies. By embedding automation, simulation-driven prioritization, and standards-based validation into VE processes, organizations can reduce dependency on human judgment while maintaining transparency, traceability, and accountability in planning decisions. This approach ensures that both efficiency and reliability are preserved without sacrificing interpretability for engineers and decision-makers.
Key insights from this research include:

Manual interventions create measurable overheads that degrade planning efficiency, increase rework, and propagate errors across simulation stages.

Systematic feature selection and prioritization enable VE systems to concentrate on critical validation points such as collision checks, robot reachability, and safety compliance, thereby reducing redundancy and improving accuracy.
Hybrid simulation frameworks allow organizations to model trade-offs between manual and automated VE workflows, providing actionable guidance for optimizing ramp-up timelines and minimizing risk.
Standardization of workflows and automation rules enhances reproducibility and comparability across projects, enabling scalable best practices in digital quality assurance.

The implications extend beyond theoretical contributions. For industry, implementing semi-automated and automated VE workflows informed by data-driven insights can enhance reliability, scalability, and sustainability in production facility planning. Furthermore, this study underscores the need for governance and organizational frameworks that ensure fairness, accountability, and workforce alignment during the transition to automation. Without such safeguards, there is a risk of bias in decision-making or uneven workload distribution across planning teams.
Future research should expand the methodology through real-world case studies across diverse industries such as aerospace, electronics, and pharmaceuticals, where facility planning complexities differ from the automotive sector. Integrating larger multimodal datasets, combining simulation logs with communication metadata and operator decision trails, will provide deeper insights into human–automation dynamics. Additionally, exploring hybrid human–AI collaboration models and assessing long-term impacts on workforce adaptation, operational resilience, and decision-making quality will help organizations develop scalable, future-proof frameworks for VE adoption.
In conclusion, reducing the over-reliance on manual processes is not only a technical requirement but a strategic necessity for achieving sustainable, efficient, and resilient facility planning systems. By leveraging structured computational frameworks, simulation-informed insights, and automation-aware workflows, organizations can transition toward a more agile, transparent, and data-driven production environment. This transformation enhances both operational performance and strategic competitiveness, positioning Virtual Engineering as a cornerstone of Industry 4.0 quality assurance.

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