INTEGRATING INDUSTRIAL ENGINEERING AND PETROLEUM SYSTEMS WITH LINEAR PROGRAMMING MODEL FOR FUEL EFFICIENCY AND DOWNTIME REDUCTION

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Abstract

This study addresses the persistent operational challenges of high fuel consumption and costly downtime in petroleum refinery environments, focusing on how the coordinated application of industrial engineering practices and linear programming (LP)–based optimisation can jointly improve these outcomes. Refinery operations typically involve complex, multistage conversion processes that are prone to inefficiencies arising from suboptimal process routing, equipment degradation, and inconsistent production planning. Motivated by these systemic issues, the present research adopts a quantitative cross-sectional, case-based approach conducted in a single enterprise refinery, integrating perceptual and objective data sources. Survey responses were collected from a diverse sample of 120 refinery personnel — including engineers, operators, maintenance technicians, and managerial staff — capturing organisational practices and capabilities related to production engineering and operational management. These perceptual constructs were complemented with plant-level operational records, including historical data on fuel consumption, throughput volumes, and downtime frequency and duration, thereby enabling a comprehensive evaluation of both human-centred practices and technical performance indicators. The study focused on four key explanatory variables: Industrial Engineering Practices, Energy-Management Capability, Maintenance and Reliability Practices, and LP-Based Optimisation Capability. Each construct was operationalised using multiple items measured on five-point Likert scales to reflect employees' assessments of procedural integration, resource utilisation, reliability culture, and modelling proficiency. The outcome variables were derived directly from refinery performance data: a Fuel-Efficiency Index calculated from total fuel consumed relative to throughput, and a Downtime Ratio reflecting the share of operational hours lost to equipment or process failures. The analytical strategy proceeded in several stages. First, descriptive statistics established baseline distributions of the constructs and performance metrics. Second, Pearson correlation analyses identified initial associations between practice constructs and operational outcomes. Third, multiple regression models were estimated to quantify the individual and combined predictive effects of the four practice constructs on fuel efficiency and downtime. The regression findings indicated that all four explanatory constructs significantly predicted the Fuel-Efficiency Index, collectively explaining 39 percent of its variance ($R^2 = 0.39$). This suggests that production planning discipline, energy-conscious operating behaviour, robust maintenance routines, and modelling capability have measurable and complementary effects on refinery energy performance. For the Downtime Ratio, the analysis revealed that Maintenance and Reliability Practices, Industrial Engineering Practices, and LP-Based Optimisation Capability were statistically significant predictors, jointly explaining 42 percent of the variance ($R^2 = 0.42$). These results reinforce the influential role of reliability-centred maintenance, structured engineering interventions, and model-informed decision-making in reducing operational disruptions and system bottlenecks.

Keywords

INTRODUCTION

The integration of industrial engineering principles with petroleum systems has become an important pathway for improving fuel efficiency and operational stability in refineries and related fuel-processing assets. Industrial engineering focuses on the design, improvement, and installation of integrated systems of people, materials, information, equipment, and energy, with the goal of achieving high productivity and quality at minimal cost. Petroleum systems, in turn, encompass the network of extraction, transportation, refining, and distribution processes that convert crude oil into useful fuels and petrochemical feedstocks. Together, these systems consume substantial amounts of energy and account for a significant share of global greenhouse gas emissions, making efficiency gains and downtime reduction a critical operational and environmental concern. Studies on industrial energy efficiency show that industry contributes roughly one-third of global energy use and greenhouse gas emissions, and that systematic engineering interventions can deliver large efficiency gains in energy-intensive sectors such as petroleum refining (Worrell et al., 2009). Refinery-level analyses further indicate that variations in unit configuration, operating practices, and crude slates lead to wide spreads in energy intensity and performance across plants (Elgowainy et al., 2014). These findings place fuel efficiency and equipment availability at the center of contemporary industrial engineering problems in the petroleum domain.

Figure 1: Integration Of Industrial Engineering Principles
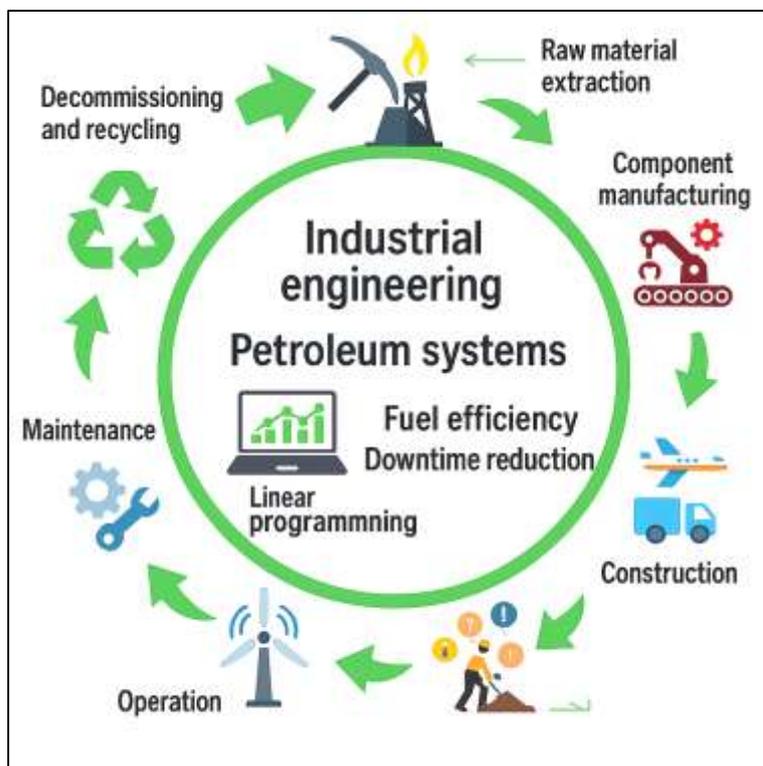
Petroleum refineries are complex process systems composed of distillation columns, cracking units, reformers, hydrotreaters, utility systems, and auxiliary equipment that must be coordinated as an integrated production network. From an operational research perspective, this complexity has motivated extensive work on mathematical programming formulations for refinery planning, scheduling, and operations management. Mixed-integer and nonlinear programming models have been developed to determine crude selection, unit operating modes, and product slates while respecting capacity, quality, and utility constraints (Alhajri et al., 2008). More recent contributions review and systematize refinery-wide optimization approaches, emphasizing the role of linear and mixed-integer linear programming (MILP) as a tractable backbone for large-scale planning problems (Abdulla & Ibne, 2021; Khor & Varvarezos, 2017). In parallel, operational planning under uncertainty has been modeled using stochastic and robust optimization frameworks to capture volatility in crude

prices, product demand, and process capacity (Habibullah & Foysal, 2021; Ribas et al., 2012). These modeling traditions show that linear programming and related optimization techniques are central tools for aligning petroleum system decisions with industrial engineering objectives, yet they often emphasize throughput and profitability more than explicit measures of fuel efficiency and downtime at the equipment level (Sanjid & Farabe, 2021).

Fuel efficiency in refinery and petroleum system contexts is commonly expressed as the ratio between useful energy embodied in products and the total primary and process energy consumed by the facility. Well-to-pump and refinery-level life-cycle assessments have quantified the energy and emission intensity of refinery operations and demonstrated that small percentage improvements in fuel efficiency translate into large absolute reductions in greenhouse gas emissions because of the high baseline energy use (Sarwar, 2021; Corrales et al., 2020). Comparative assessments of resource efficiency across different refinery configurations highlight that unit-level process integration, heat recovery, and hydrogen management substantially influence overall energy performance (Han et al., 2015). At the systems level, process-level energy efficiency measures, such as furnace upgrades, improved heat-exchanger networks, and better process control, have been evaluated in terms of long-term greenhouse gas mitigation potential, demonstrating measurable reductions in emissions when integrated into long-range planning models (Musfiqur & Saba, 2021; Talaei et al., 2020). Operational studies using data envelopment analysis and related techniques show that many refineries operate below best-practice frontiers in terms of energy, throughput, and environmental performance, indicating a quantitative improvement space for fuel efficiency (Atris, 2020; Omar & Rashid, 2021). These strands of research underscore that fuel efficiency is both a thermodynamic and managerial phenomenon, shaped by process design, operating strategies, and decision-support tools.

Downtime reduction represents a second major pillar of performance in industrial systems, particularly in capital-intensive, continuous-process industries such as oil refining. Unplanned equipment stoppages, extended changeovers, and maintenance-related outages compromise throughput, raise unit costs, and can create cascading bottlenecks in upstream and downstream units. Reliability and maintenance engineering literature has long emphasized structured approaches for maintaining functional integrity and availability, including reliability-centered maintenance (RCM) and risk-centered maintenance frameworks that link failure modes to maintenance policies and risk criteria (Selvik & Aven, 2011). At the same time, optimization-oriented reviews highlight that maintenance decisions can be modeled using stochastic and deterministic optimization, integrating preventive, predictive, and corrective maintenance into production planning (de Jonge & Scarf, 2020). Case studies from refinery environments illustrate how RCM-based preventive maintenance programs can be tailored to critical process units and utility systems, enabling more structured inspection intervals and spare-part planning (Nakamanuruck et al., 2017). As these approaches mature, the connection between maintenance strategies, downtime profiles, and fuel efficiency becomes increasingly visible, since poorly planned stoppages and asset degradation often lead to sub-optimal loading, off-spec products, and elevated energy consumption.

Within industrial engineering, the measurement and continuous improvement of equipment efficiency have been strongly influenced by the concepts of total productive maintenance (TPM) and overall equipment effectiveness (OEE). TPM provides a structured program for involving operators and maintenance personnel in jointly pursuing zero defects, zero accidents, and zero breakdowns, with OEE serving as a key performance indicator capturing availability, performance rate, and quality yield (Ahuja & Khamba, 2009; Redwanul et al., 2021). OEE-based metrics have been extensively studied and refined, with frameworks describing how different types of losses such as breakdowns, minor stoppages, speed losses, and quality losses contribute to overall performance shortfalls (Tarek & Praveen, 2021; Muchiri & Pintelon, 2008). Maintenance performance measurement frameworks extend these ideas to link maintenance process indicators and results indicators with strategic objectives such as cost, reliability, and responsiveness (Zaman & Momena, 2021; Muchiri et al., 2011). More recent systematic reviews show growing interest in OEE within lean manufacturing and optimization contexts, and discuss numerous variants and extensions tailored to specific industries and digitalized production environments (Rachman & Ratnayake, 2019; Rony, 2021). Additional studies investigate how OEE-based assessments can be used to identify maintenance improvement potential, refine

maintenance policies, and better understand the relationship between equipment behavior and productivity (En-Nhaili et al., 2016). Together, these contributions provide conceptual and analytical foundations for linking downtime reduction strategies to quantifiable performance indicators.

The conceptual and theoretical underpinnings of downtime reduction and fuel efficiency improvement frequently draw on lean production, total productive maintenance, and continuous improvement philosophies. Lean and TPM signal the importance of waste elimination, standardization, and operator involvement, framing downtime and energy overuse as forms of muda that can be systematically removed through structured problem solving. Empirical studies on TPM demonstrate positive relationships between TPM practices and manufacturing performance, including higher equipment availability, improved quality, and lower unit costs (Ahuja & Khamba, 2008). Lean maintenance and OEE-based improvement approaches show that integrating maintenance with production objectives supports better prioritization of activities and a clearer focus on the most critical loss categories (AlZain et al., 2020). Reviews of OEE and related indicators further suggest that performance metrics grounded in these frameworks can be adapted to continuous-process industries where availability and speed losses dominate overall performance (Ng Corrales et al., 2020). For complex process plants, such as refineries, these theories offer a conceptual basis for linking maintenance policies and operational practices to measurable changes in downtime, throughput, and resource utilization, although their implementation often requires sector-specific adaptation.

Within the petroleum industry, these industrial engineering and continuous improvement frameworks have been applied to address the particular challenges of operating complex assets under tight safety, environmental, and cost constraints. Studies on lean adoption in the petroleum sector report increasing interest in lean tools and principles for enhancing process flow, work standardization, and waste reduction in both upstream and downstream operations (Ratnayake & Chaudry, 2017). For operating petroleum assets, lean Six Sigma (LSS) methodologies have been proposed as structured approaches for stabilizing process performance and quantifying improvements in key performance indicators such as downtime, defect rates, and throughput (Gao et al., 2008; Shaikh & Aditya, 2021). More comprehensive frameworks describe how LSS can support continuous and incremental improvement in the oil and gas sector by embedding data-driven problem solving in day-to-day operational management (AlZain et al., 2020; Sudipto & Mesbaul, 2021). In parallel, refinery-specific energy and emission studies continue to highlight the importance of process-level efficiency improvements and operational best practices for meeting environmental and economic performance requirements (Ljungberg & Kördell, 2017; Zaki, 2021). These streams of work collectively suggest that integrating industrial engineering concepts with petroleum systems offers a coherent way to address both fuel efficiency and downtime challenges in refinery environments (Hozyfa, 2022; Al Amin, 2022).

Although mathematical programming models in refinery planning and operations demonstrate strong capability in optimizing production, blending, and utility systems, they rarely incorporate rich representations of downtime behavior, maintenance constraints, and human-centered industrial engineering considerations. Refinery-wide optimization reviews document how linear and mixed-integer models are used to coordinate crude selection, unit loading, and product distribution under numerous technical constraints, but most objective functions are formulated around profit maximization or cost minimization with relatively simplified availability assumptions (Forman et al., 2014; Arman & Kamrul, 2022). At the same time, maintenance optimization and OEE-based studies develop detailed treatments of downtime, failure behavior, and performance losses, but are not always explicitly linked to refinery-specific linear programming models (Han et al., 2015; Mohaiminul & Muzahidul, 2022). There is also limited empirical evidence that combines survey-based assessments of maintenance, lean, and LSS practices with quantitative linear programming models calibrated for particular petroleum case studies. As a result, an opportunity arises to construct an integrated research design that uses a quantitative, cross-sectional, case-study–based survey with Likert-scale variables and statistical analysis to characterize the current state of industrial engineering and maintenance practices, while simultaneously formulating a linear programming model that captures fuel efficiency and downtime-related constraints in the same petroleum system. In this context, the present study, titled "Integrating Industrial Engineering and Petroleum Systems with Linear Programming Model for Fuel Efficiency and Downtime Reduction," focuses on developing and empirically evaluating such an

integrated framework within a real-world petroleum case, using descriptive statistics, correlation analysis, regression modeling, and linear programming to address defined research questions and hypotheses (Jasiulewicz-Kaczmarek, 2017; Jasiulewicz-Kaczmarek & Żywica, 2017).

The overarching objective of this study is to systematically examine how the integration of industrial engineering practices with a linear programming model within a petroleum system can enhance fuel efficiency and reduce downtime in a real operating environment. To achieve this overarching aim, the study first seeks to document and quantify the current level of industrial engineering adoption in the selected petroleum facility, including practices related to lean process management, maintenance planning, performance measurement, and continuous improvement. In parallel, the study aims to assess the extent to which linear programming or closely related optimization models are used to support decisions on production planning, energy management, and capacity allocation, and to determine how formally these tools are embedded in routine operational decision-making. Building on this diagnostic perspective, the research establishes a set of specific objectives that structure the empirical and modeling work. One objective is to construct and validate a measurement framework, based on Likert-scale survey items, that captures key dimensions of industrial engineering integration and optimization-supported planning as perceived by engineers, maintenance personnel, and operations managers in the case-study facility. A second objective is to gather quantitative operational data related to fuel consumption, production levels, and downtime events, and to compute a set of fuel-efficiency and downtime performance indicators that can serve as dependent variables in subsequent analyses. A third objective is to apply descriptive statistics, correlation analysis, and regression modeling to evaluate the relationships between industrial engineering practices, optimization-supported planning, and observed performance outcomes, thereby testing the formulated research hypotheses in a structured way. A fourth objective is to formulate a linear programming model that represents the main production and utility processes of the case-study petroleum system, parameterized by the collected operational data, with an explicit objective of improving fuel efficiency and reducing downtime-related capacity losses under realistic constraints. A fifth objective is to compare the performance of current operating patterns with the optimized solutions generated by the linear programming model, quantifying potential gains in fuel efficiency and reductions in downtime within the modeled decision space. Together, these objectives define a coherent empirical and analytical pathway that guides the design of the survey instrument, the selection of performance indicators, the statistical analysis, and the optimization modeling at the core of the study.

LITERATURE REVIEW

The literature on industrial engineering applications in petroleum systems reveals a progressive shift from isolated efficiency initiatives toward more integrated, model-based approaches that jointly address operational performance, energy use, and reliability. Early studies tend to treat production planning, maintenance scheduling, and energy management as largely separate domains, with distinct tools and performance indicators guiding each functional area. Over time, however, the persistent challenges of high fuel consumption, complex process interactions, and costly downtime in refineries and related facilities have driven researchers to explore stronger linkages between process optimization, maintenance engineering, and continuous improvement philosophies. Within this evolving landscape, linear and mixed-integer programming models have become central to refinery planning and scheduling, enabling detailed representation of process units, product quality constraints, and utility systems within a single optimization framework. Parallel developments in reliability-centered maintenance, total productive maintenance, and overall equipment effectiveness have provided structured ways to characterize equipment losses, prioritize maintenance actions, and quantify the impact of downtime on throughput and cost. Lean and Six Sigma approaches add another layer by promoting waste elimination, standardization, and data-driven problem solving, which directly touch on phenomena such as avoidable energy losses, changeover delays, and recurring failure modes. Despite these advances, much of the existing work still analyzes fuel efficiency and downtime through different methodological lenses and data sources, making it difficult to capture how industrial engineering practices, quantitative optimization, and real-world operational contexts interact in a unified system. The present literature review is therefore organized to build a coherent bridge across these strands. It first examines industrial engineering approaches and performance frameworks that

are particularly relevant for fuel-intensive, continuous-process industries such as petroleum refining. It then reviews the role of linear programming and related optimization techniques in modeling refinery operations and energy use. Next, it introduces the main theoretical lens used to conceptualize petroleum facilities as integrated socio-technical systems. Finally, it develops two complementary conceptual frameworks that explicitly connect industrial engineering practices and linear programming models to fuel efficiency and downtime reduction, thereby establishing a structured foundation for the empirical research design and hypothesis development in this study.

Industrial Engineering Approaches to Energy

Industrial engineering has increasingly been recognised as a central discipline for analysing and improving the performance of energy-intensive production systems, and this is especially visible in petroleum refining and gas-processing operations. These systems are characterised by highly integrated flows of crude, intermediates, and utilities, where changes in one unit ripple through the entire network of distillation columns, reactors, heat exchangers, and compression trains. From an industrial-engineering standpoint, energy and fuel behaviour cannot be treated as a separate "utility topic" but must be embedded in production planning, capacity utilisation, and supply-chain coordination. Strategic case work in energy-intensive process industries shows that many firms still treat energy mainly as a cost item rather than as a strategic resource that shapes competitiveness, risk exposure, and long-term asset configuration (Rudberg et al., 2013). By analysing energy systems simultaneously from strategic, energy-system utilisation, and revenue-generation perspectives, that study demonstrates that energy decisions influence product mix, technology choices, and contractual arrangements with external energy markets, not just operating expenses. In parallel, a systematic review of industrial energy management identifies five interlinked elements strategy and planning, implementation and operation, controlling, organisation, and culture that together form a comprehensive conceptual framework for energy management in industry (Omar & Ibne, 2022; Sanjid & Zayadul, 2022; Schulze et al., 2016). This framework is directly relevant to petroleum systems because it positions energy performance as an integrated management problem in which industrial engineers design processes, indicators, and feedback loops that link shop-floor operations with corporate strategy.

Figure 2: Application of industrial engineering, energy management
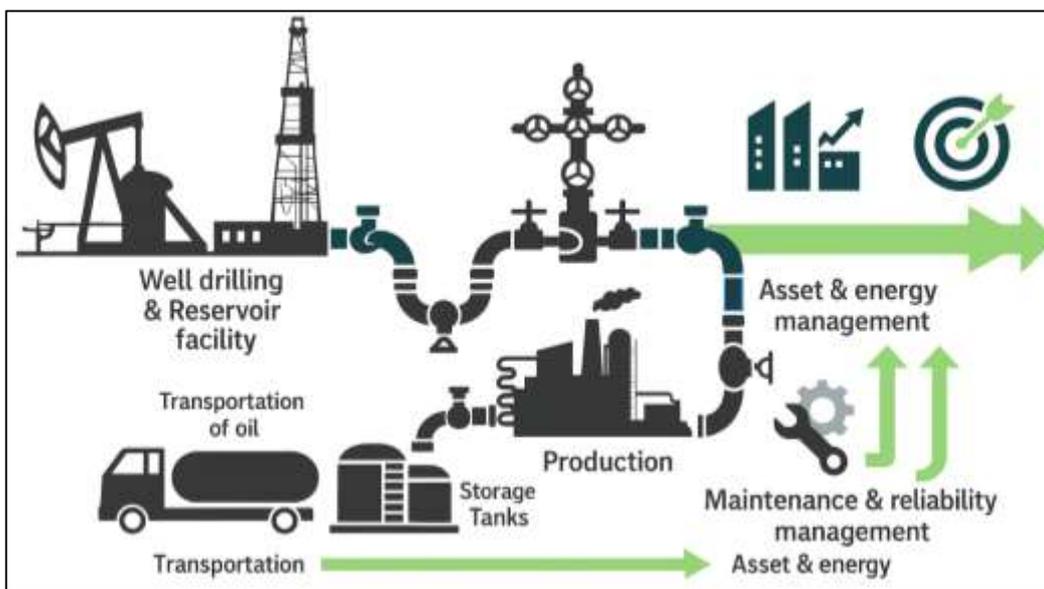
Within this broader energy-management paradigm, standards-based management systems and improvement methodologies have emerged as practical vehicles for embedding industrial-engineering thinking into the daily routines of engineers, operators, and managers in energy-intensive plants. ISO 50001 provides a generic structure for energy policy, energy review, baselining, indicators, and plan–do–check–act cycles, but empirical studies show that the standard gains real traction only when

supported by robust analytical tools and cross-functional teamwork. A Lean Six Sigma-based energy management model aligned with ISO 50001 illustrates how the define–measure–analyse–improve–control (DMAIC) cycle can be used to structure energy reviews, prioritise significant energy uses, and translate statistical analysis into targeted interventions in industrial plants (Mkhaimer et al., 2017). Although the reported case focuses on a pharmaceutical company rather than a refinery, the underlying logic combining process mapping, data-driven diagnosis, and disciplined project execution maps closely onto the challenges faced in petroleum operations, where fuel use is tightly coupled to throughput, feed quality, and equipment condition (Hasan, 2022; Mominul et al., 2022). At the technology and process-design level, industrial-engineering perspectives are equally visible in work on process intensification for the oil and gas industry. A recent technological framework systematically classifies intensification opportunities, links them to specific unit operations, and evaluates alternatives in terms of energy efficiency, compactness, controllability, and safety (Abdulrahman et al., 2020; Rabiul & Praveen, 2022; Farabe, 2022). This approach positions process intensification as a structured design and decision problem in which industrial engineers use modelling and optimisation to explore trade-offs between fuel consumption, capacity, emissions, and capital cost across the entire petroleum value chain (Roy, 2022; Rahman & Abdul, 2022; Razia, 2022).

A complementary stream of industrial-engineering research connects energy performance with maintenance and reliability-centred asset management, which are crucial determinants of both fuel efficiency and downtime in petroleum systems. In refineries and gas plants, critical equipment such as pumps, compressors, furnaces, turbines, and large rotating machinery are simultaneously major energy consumers and key bottlenecks for production (Maniruzzaman et al., 2023; Zaki, 2022; Kanti & Shaikat, 2022). When these assets degrade, foul, or drift away from their design envelopes, plants experience higher specific fuel consumption, more frequent trips, and longer outages. A reliability-based maintenance strategy model for process plants proposes a structured approach in which reliability-centred maintenance is implemented using failure data, criticality analysis, and analytical hierarchy process to select appropriate policies (corrective, preventive, or predictive) for each asset class (Arif Uz & Elmoon, 2023; Sanjid, 2023; Vishnu & Regikumar, 2016). The case study demonstrates that treating maintenance strategy selection as a multi-criteria decision problem leads to better availability and performance than ad-hoc mixes of scheduled and breakdown maintenance. For petroleum systems, this line of work motivates a tighter integration between maintenance planning, energy performance, and production scheduling: industrial engineers can use reliability data and criticality scores to identify where improved maintenance policies will yield the largest combined benefits in reduced fuel waste and avoided downtime (Sanjid & Sudipto, 2023; Tarek, 2023; Shahrin & Samia, 2023). Conceptually, this provides a foundation for the present study's focus on integrating industrial-engineering methods and petroleum systems analysis, because it highlights how quantitative models can simultaneously support fuel-efficiency gains and downtime reduction across complex, capital-intensive processing networks.

Linear Programming Models for Fuel-Efficient

Linear and mixed-integer linear programming have long provided the analytical backbone for optimizing large-scale industrial systems, and petroleum refineries are among the most prominent beneficiaries of these tools. Enterprise-wide optimization views the refinery not as a collection of isolated units, but as a tightly coupled production–logistics system in which crude selection, unit throughputs, product blending, and utility consumption must be coordinated under economic and technical constraints (Grossmann, 2005; Muhammad & Redwanul, 2023; Muhammad & Redwanul, 2023). Within this paradigm, linear programming (LP) models approximate complex physicochemical behaviour with linear yield relationships, capacity bounds, and quality constraints, allowing engineers to compute globally optimal operating plans within seconds even for thousands of variables and constraints. For fuel-efficiency goals, such models embed energy-use coefficients for heaters, pumps, compressors, and ancillary systems, so that the objective function simultaneously maximizes margin and minimizes energy intensity at the refinery or network level (Fernández & Carrillo Le Roux, 2011). From a downtime-reduction perspective, LP structures also provide a natural way to encode maintenance windows, minimum up/down times, turnaround cycles, and redundancy options, thus enabling planners to test how alternative industrial engineering policies such as rescheduling

changeovers, decoupling critical paths, or rerouting material through parallel units affect throughput and equipment utilisation. These formulations can also incorporate penalty terms for unmet demand, excessive start–stop operations, or operation near constraint limits, thereby reflecting the practical engineering insight that unstable operating regimes tend to be both energy intensive and reliability poor. In the context of the present study, these capabilities make LP a particularly suitable framework for integrating industrial engineering decisions with petroleum process constraints to evaluate trade-offs between fuel savings, capacity utilisation, and risk of bottlenecks across the refinery system. In practical refinery settings, this means that planners can rapidly compare alternative configurations of crude slates, throughput levels, and energy-management strategies, using the LP outputs to support structured what-if analyses during planning meetings and cross-functional coordination between operations, maintenance, and energy-management teams.

Figure 3: Linear programming models for fuel-efficient and reliable petroleum operations
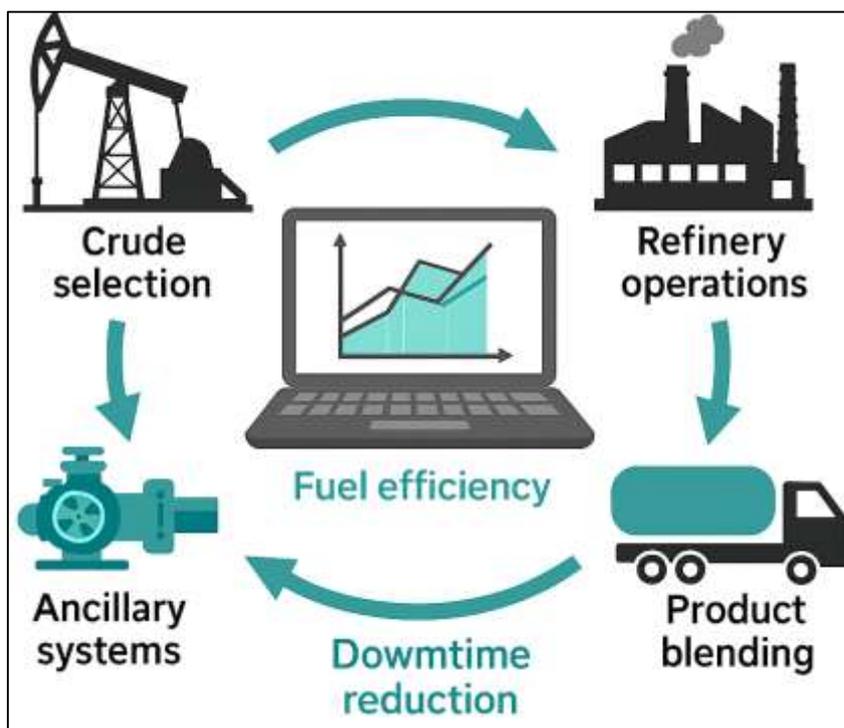
Building on these foundational ideas, refinery-planning researchers have progressively embedded more detailed representations of refinery operations into mixed-integer linear programming (MILP) models. Early fixed-yield models have been extended to incorporate multiple time periods, storage dynamics, blending recipes, and product slate flexibility, allowing planners to evaluate fuel-efficient campaigns while respecting inventory, logistics, and product-quality requirements (Méndez et al., 2006; Razia, 2023; Srinivas & Manish, 2023). By explicitly representing discrete decisions such as unit start-ups, shutdowns, changeovers, tank-switching operations, and grade transitions with binary variables, MILP models can capture the downtime implications of operational sequencing and equipment allocation choices that are invisible in purely continuous LP formulations (Li et al., 2020; Sudipto, 2023; Zayadul, 2023). For fuel efficiency, MILP formulations support piecewise linear approximations of nonlinear energy-consumption curves and heat-integration opportunities, enabling the optimizer to bias production toward operating regions where specific energy use per barrel is lowest while still satisfying multi-period demand and quality specifications. At the same time, integration of blending and scheduling decisions in a single MILP framework makes it possible to identify schedules that reduce the number of off-spec products, reblends, and deferred shipments, which in turn lowers avoidable flaring, heater reprocessing, and associated energy waste. These more granular models therefore bridge the gap between high-level enterprise planning and detailed operational scheduling, and they illustrate how linear programming paradigms can be tailored to

reflect both fuel-efficiency metrics and downtime-sensitive industrial engineering constraints such as overall equipment effectiveness, mean time between failures, and utilisation of critical bottleneck units. For case-study oriented research, these models provide a transparent link between survey-based measures of operational practices and the simulated effects of different scheduling policies, allowing researchers to quantify how improved coordination, preventive-maintenance timing, or staffing patterns might translate into measurable reductions in idle capacity and unplanned outages when embedded within a realistic refinery flowsheet.

A more recent stream of work extends LP and MILP methodologies to multi-refinery networks, nonlinear process models, and uncertain operating environments, all of which are central to contemporary discussions of fuel efficiency and reliability in petroleum systems. Robust-planning models for multisite refinery networks incorporate uncertainty in crude availability, product demand, and price by seeking solutions that remain feasible and near-optimal across predefined disturbance sets, thereby protecting against energy-inefficient operating modes and unplanned shutdowns triggered by market or supply volatility (Al-Qahtani & Elkamel, 2010). Complementary studies replace traditional fixed-yield unit models with empirically calibrated nonlinear representations of crude distillation and catalytic cracking, which are then embedded in planning models to improve predictions of product yields, energy consumption, and bottleneck locations (Guerra Fernández & Carrillo Le Roux, 2011). These advances have been synthesised in recent reviews of planning and scheduling for petroleum and petrochemical production, which emphasise that the practical value of LP-based optimisation depends on its ability to accommodate real refinery complexities such as changing fuel specifications, integration with petrochemical units, and coordination across multiple time scales from tactical planning to day-to-day scheduling (Li et al., 2020). In such a setting, linear and mixed-integer programming models serve not merely as theoretical constructs, but as decision-support tools that allow engineers and managers to explore how alternative crude slates, unit configurations, and maintenance strategies influence energy intensity, downtime risk profiles, and system-wide resilience. Collectively, this body of work demonstrates that contemporary linear programming-based approaches are no longer limited to simplified, single-period refinery snapshots; instead, they provide a rich mathematical infrastructure for analysing how integrated industrial engineering and petroleum-system decisions shape fuel efficiency, downtime risk, and overall performance in complex refinery operations. These features are directly relevant to the objectives of the present empirical study.

Theoretical Framework of Operations Management Perspective

From a theoretical standpoint, the present study views a petroleum refinery as a *production system* embedded in wider technical, economic, and environmental networks. Systems theory conceptualises organisations as open systems that exchange materials, energy, and information with their environment, and whose behaviour emerges from the interaction of interdependent subsystems rather than from isolated components. In this spirit, production systems theory emphasises flows, feedback loops, and structural configurations, arguing that the design of the production system governs cost, quality, flexibility, and learning over time (Fleury & Fleury, 2007). For refinery operations, this implies that fuel efficiency and downtime cannot be fully understood at the level of individual heaters, pumps, or distillation columns; instead, they arise from system-wide patterns such as bottlenecks, capacity mismatches, heat-integration structures, and maintenance policies. General systems thinking extends this view by highlighting that managerial decisions should focus on relationships, boundaries, and feedback, rather than on isolated events or single-point optimisations (Mele et al., 2010). In practical terms, a system-level fuel-efficiency indicator can be written as

$$\eta_{\text{fuel}} = \frac{\sum p E_p^{\text{useful}}}{\sum_i E_i^{\text{fuel}}},$$

where the numerator aggregates useful energy embodied in products and the denominator aggregates all fuel and utility energy inputs across units. When combined with a downtime ratio

$$D = \frac{T_{\text{downtime}}}{T_{\text{planned}}},$$

these quantities provide system-level state variables whose behaviour over time is governed by the configuration and management of the production system. The theoretical implication is that improving

η_{fuel} and reducing D requires interventions at the level of system design and coordination, not merely equipment-level upgrades, which justifies adopting systems theory as a guiding lens for constructing the conceptual model in this research.

Systems theory is complemented in this study by a *socio-technical systems* (STS) perspective, which stresses the joint optimisation of social and technical subsystems. STS theory argues that organisational outcomes depend on the alignment between human roles, work practices, and technical artefacts, and that designs focusing solely on technology frequently underperform because they neglect issues such as usability, coordination, and local improvisation (Baxter & Sommerville, 2011). In a refinery context, this means that the benefits of advanced industrial engineering practices or linear programming models materialise only when planners, engineers, and operators understand and trust the models, and when procedures and responsibilities are adjusted to support model-based decision-making. To capture dynamic interactions between structure and behaviour, the study also draws on *system dynamics* as a structural theory of operations management, which views operations systems as networks of stocks, flows, feedback loops, and delays (Größler et al., 2008). From this perspective, variables such as fuel consumption, throughput, backlog, and maintenance workload are accumulations that evolve according to differential or difference equations, and policies such as throughput increases, maintenance deferrals, or energy-saving projects generate time-delayed and often non-intuitive effects. For example, aggressive throughput increases may temporarily improve utilisation but later trigger congestion, quality problems, or equipment stress that raise both downtime and specific fuel consumption. System-dynamics theory therefore reinforces the view that the refinery must be conceptualised as a feedback-rich socio-technical system, in which linear programming models are embedded as decision rules that interact with human behaviour, organisational routines, and physical constraints. This multi-level theoretical framing supports the empirical design of the study, which measures perceived industrial engineering practices and planning routines, while also representing structural process constraints in an explicit optimisation model.

Figure 4: Theoretical framework illustrating systems and operations management perspectives

$$\eta_{fuel} = \sum p \, E^{uf}_{ul_i} \cdot E_{fuel}$$

$$D = \frac{T_{downtime}}{T_{planned}}$$
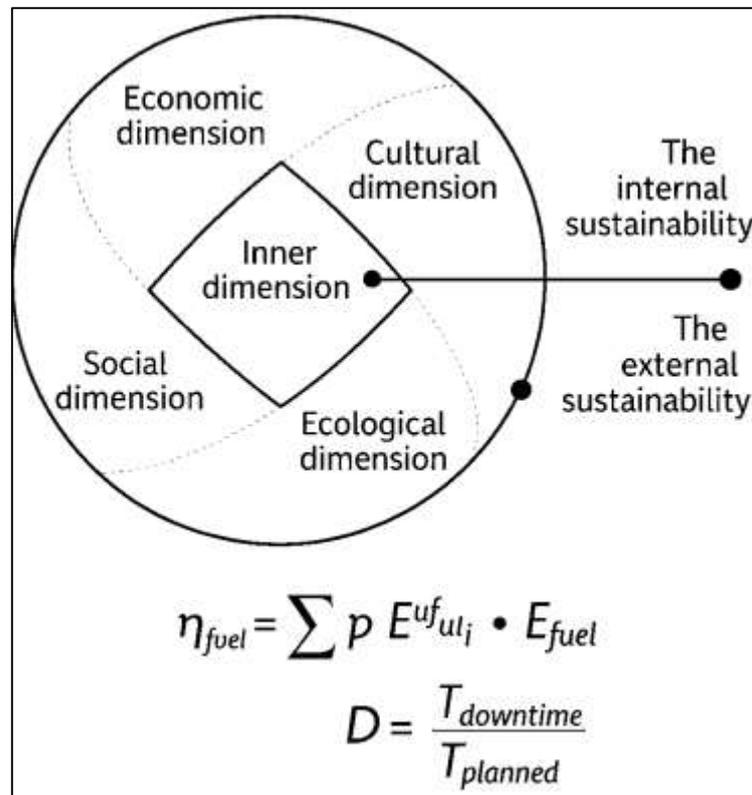
To connect these system-theoretic ideas to operational decision-making about fuel efficiency and downtime, the study adopts the *Theory of Constraints* (TOC) as a complementary operations-

management framework. TOC posits that system performance is predominantly determined by a small number of constraints, and that improvement efforts should focus on these leverage points through the five focusing steps: identify the constraint, decide how to exploit it, subordinate everything else, elevate the constraint, and repeat (Panizzolo & Garengo, 2013). In quantitative terms, TOC links throughput (TH), inventory (I), and operating expense (OE), often expressing performance through relationships such as

$$\text{Profit} = TH - OE,$$

while emphasising that local efficiency metrics can be misleading if they obscure the behaviour of the system's constraint. When combined with classical industrial engineering indicators such as overall equipment effectiveness

$$OEE = A \times P \times Q,$$

where A denotes availability, P performance rate, and Q quality yield, TOC provides a conceptual rationale for targeting improvements at bottleneck units whose downtime and energy characteristics dominate the behaviour of the whole system. Within the linear-programming framework used in this study, such theoretical insights are operationalised by representing bottlenecks and maintenance-related capacity limits as binding constraints, and by incorporating fuel costs and downtime penalties in the objective function, for example

$$\min Z = \sum_i c_i F_i + \lambda \sum_k T_k^{\text{down}},$$

where F_i is fuel use in unit i, T_k^{down} downtime at critical resources k, and λ a weighting parameter reflecting the relative importance of downtime. In this way, systems theory, socio-technical systems thinking, system dynamics, and TOC jointly inform the conceptual framework by explaining why integrating industrial engineering practices with a linear-programming model is theoretically appropriate for analysing and improving fuel efficiency and downtime in petroleum refinery systems.

Conceptual Framework

Figure 5: Hypothesised relationships between industrial energy engineering capability
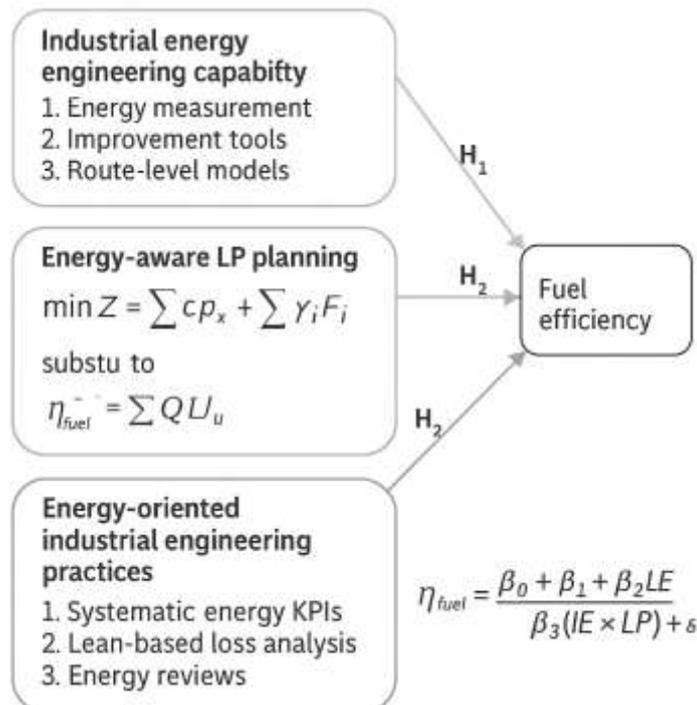
A first strand in the conceptual framework treats fuel efficiency in petroleum operations as an outcome of how industrial engineering practices structure measurement, control, and continuous improvement. Work on energy-aware production management shows that energy efficiency can and should be handled as a performance dimension alongside cost, quality, and delivery, supported by key

performance indicators (KPIs), ICT systems, and formal routines (Bunse et al., 2011). In this view, each production or utility unit u is associated with an energy performance indicator such as

$$EPI_u = \frac{E_u}{Q_u},$$

where E_u denotes fuel or utility energy consumed and Q_u denotes the associated throughput (for example, barrels processed or tonnes of product). At refinery level, a composite fuel-efficiency index can then be defined as

$$\eta_{\text{fuel}} = \frac{\sum_u Q_u \cdot LHV_u}{\sum_u E_u},$$

with LHV_u representing the lower heating value of each product stream. The conceptual framework assumes that industrial engineering practices such as systematic energy KPIs, lean-based loss analysis, and cross-functional energy reviews improve data quality, reveal waste, and stabilise operating conditions, thereby raising η_{fuel}. Studies on modelling energy consumption in manufacturing systems reinforce this logic by arguing that transparency of energy flows at machine, line, and factory level is a prerequisite for effective optimisation (Seow & Rahimifard, 2011). Accordingly, the first block of the conceptual model groups together energy-management routines, measurement systems, and improvement tools as a latent construct "industrial energy engineering capability," hypothesised to exert a positive effect on fuel-efficiency indicators at unit and system scale.

A second strand of the framework links micro-level modelling of energy behaviour to meso-level process chains and, ultimately, to production planning decisions. Research on energy-efficient manufacturing emphasises that energy consumption depends not only on individual machine tools, but also on how operations are sequenced, buffered, and controlled across entire manufacturing systems (Salonitis & Ball, 2013). At this level, energy use for a production route r can be represented as

$$E_r = \sum_{k \in r} P_k t_k,$$

where P_k is the average power demand of operation or resource k and t_k the processing or waiting time experienced under a given schedule. Conceptual frameworks for modelling energy consumption in manufacturing argue that such expressions must be embedded in hierarchical models, where product, process, and system decisions jointly determine the distribution of P_k and t_k over time (Seow & Rahimifard, 2011). In parallel, systematic reviews of energy-oriented production planning identify classes of decision-support models in which energy objectives such as minimising E_r or energy cost are treated on a par with classical economic goals, but also show that many implementations still omit organisational practices and behavioural aspects (Terbrack et al., 2021). Bringing these insights together, the present conceptual framework posits that detailed energy modelling and mapping are intermediate mechanisms between industrial energy engineering capability and fuel-efficiency outcomes: plants that invest in structured energy data and route-level models are better positioned to embed fuel-related constraints and objectives into their planning models, thereby transforming local engineering insights into system-level efficiency improvements.

The third strand explicitly connects energy-oriented industrial engineering practices with linear-programming–based planning, defining the core integration logic of this study. Mathematically, an energy-aware linear programming (LP) model for refinery operations can be expressed in stylised form as

$$\min Z = \sum_p c_p x_p + \sum_i \gamma_i F_i,$$

subject to material balances, capacity limits, product-quality specifications, and non-negativity of decision variables x_p (production and flow decisions) and F_i (fuel use in unit i). Reviews of energy-oriented production planning show that when such models explicitly incorporate energy indicators and price signals, they can steer production towards schedules and routing patterns with lower energy intensity while still satisfying demand and technical constraints (D'Adamo et al., 2021). Extensions of lot-sizing and scheduling with time-dependent energy prices demonstrate how binary and continuous decision variables can capture both production quantities and the timing of operations, enabling planners to exploit off-peak tariffs and avoid energy-intensive peak configurations (Wichmann et al.,

2019). Conceptually, the proposed framework treats "LP-based optimisation capability" as a second latent construct, reflecting the extent to which refineries embed such models in operational decision-making. The joint effect of industrial energy engineering capability and LP-based optimisation on fuel efficiency can then be represented in a regression-style structural equation, for example

$$\eta_{\text{fuel}} = \beta_0 + \beta_1 IE + \beta_2 LP + \beta_3 (IE \times LP) + \varepsilon,$$

where IE and LP are latent scores for industrial engineering and optimisation capability. Evidence from both energy-modelling and optimisation literature implies $\beta_1 > 0$ and $\beta_2 > 0$, while the interaction term β_3 captures the theorised complementarity: industrial engineering practices create accurate, actionable energy data, and LP models transform that data into globally consistent operating policies (Seow & Rahimifard, 2011). Finally, comprehensive reviews of energy-efficient and sustainable manufacturing systems argue that such integrated, model-based approaches are necessary to align machine-level improvements with system-level planning and environmental goals, reinforcing the theoretical plausibility of this combined construct for fuel-efficiency improvement in petroleum refineries (Seow & Rahimifard, 2011).

Conceptual Framework II: Integrated Maintenance–Production Modeling for Downtime Reduction
A second conceptual foundation for this study links reliability-centred maintenance, industrial engineering metrics, and downtime behaviour in petroleum production and refining systems. In continuous energy and process plants, unplanned stoppages translate directly into production losses, fuel waste, and safety risks; therefore, maintenance policy becomes a core driver of both availability and fuel efficiency rather than a purely supportive function. Reliability-centred and proactive preventive maintenance (PM) programmes have been shown to reduce labour, spare-parts, and downtime costs by shifting organizations away from reactive "run-to-failure" practices toward reliability-focused cultures that anticipate and prevent failures (Eti et al., 2006). In this framework, downtime is conceptualized as the fraction of planned operating time lost due to stoppages, $D = \frac{T_{\text{down}}}{T_{\text{up}} + T_{\text{down}}}$, while equipment availability is given by $A = \frac{MTBF}{MTBF + MTTR}$, where $MTBF$ is mean time between failures and $MTTR$ is mean time to repair. Proactive PM policies increase $MTBF$ and can reduce *effective MTTR* through better planning and standardization, thereby increasing availability and reducing downtime intensity for critical petroleum assets such as pumps, compressors, and distillation units (Afefy, 2010). Within this conceptual framework, maintenance strategy, reliability metrics, and downtime outcomes form a causal chain: stronger reliability-centred maintenance capability improves component reliability and maintainability, which in turn raises availability and decreases unplanned stoppages, ultimately supporting lower specific fuel consumption per unit of output in petroleum systems.

Figure 6: Integrated maintenance–production modeling for downtime reduction in petroleum operations.
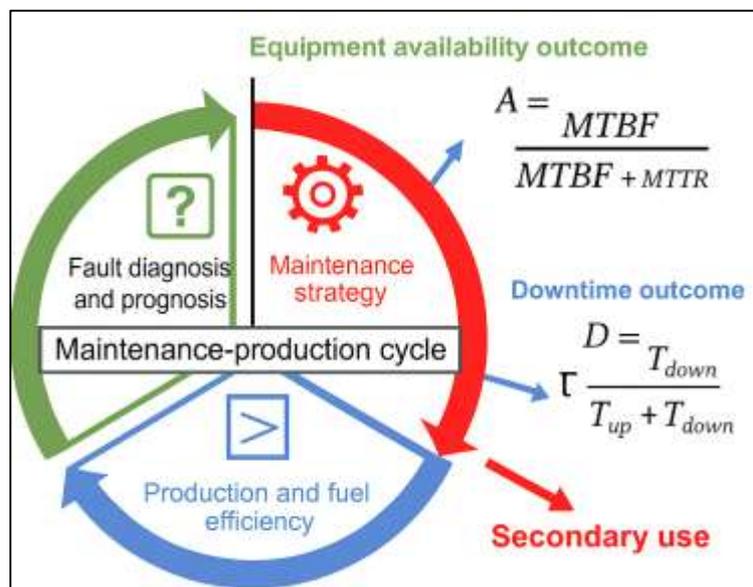
At the operational level, a substantial body of industrial engineering research demonstrates that integrating production scheduling and preventive maintenance decisions into a single optimization structure yields better performance than treating them separately. In single-machine and flow-line settings, integrated models simultaneously decide job sequences and PM timing, explicitly accounting for the trade-off between reserving capacity for maintenance and risking stochastic failures that cause unplanned downtime (Cassady & Kutanoglu, 2005). Conceptually, these models treat downtime as an endogenous variable driven by maintenance and scheduling choices rather than an exogenous disturbance. A typical cost-oriented objective function can be expressed as

$$C_{\text{tot}} = C_{\text{prod}} + C_{\text{PM}} + C_{\text{CM}} + C_{\text{DT}},$$

where C_{prod} is production cost, C_{PM} preventive maintenance cost, C_{CM} corrective maintenance cost, and $C_{\text{DT}} = c_{\text{dt}} E[T_{\text{down}}]$ is expected downtime cost with downtime unit penalty c_{dt}. In integrated maintenance–scheduling models, PM intervals, repair policies, and job sequences are chosen to minimize C_{tot} subject to capacity and due-date constraints, often under machine degradation or Weibull failure assumptions (Pan et al., 2010). This provides a conceptual template for the present research: in petroleum facilities, preventive and corrective maintenance activities on critical process units are not independent from throughput and energy-use decisions; instead, they must be co-optimized because every maintenance action simultaneously consumes capacity, alters failure risk, and modifies the expected profile of planned versus unplanned downtime.

More recently, integrated production–maintenance formulations have been extended to include energy or fuel consumption explicitly, making them particularly relevant for petroleum and fuel-intensive operations. In these models, processing times and energy use depend on machine health, and maintenance decisions affect not only availability but also the energy intensity of production (Yildirim & Nezami, 2014). The resulting optimization problem can be expressed within a linear or mixed-integer linear programming structure where the objective is to minimize a composite cost function:

$$\min Z = \sum_t (c_q Q_t + c_f F_t + c_m M_t + c_d D_t),$$

with Q_t representing production quantity, F_t fuel or energy consumption, M_t planned maintenance effort, and D_t downtime in period t, while c_q, c_f, c_m, c_d are the respective cost coefficients. Constraints link available capacity to maintenance and reliability, for example $Q_t \leq \text{Cap} \cdot A_t$, where A_t is period-specific availability determined by maintenance history and degradation state (Pan et al., 2010). In the context of petroleum systems, this conceptual framework implies that the linear programming model in this study should jointly represent production, maintenance, and downtime variables so that optimal solutions balance fuel efficiency, planned maintenance windows, and penalties for unplanned stoppages. By embedding reliability-centred maintenance concepts (Afefy, 2010) and proactive preventive culture (Eti et al., 2006) into an integrated linear optimization structure, the framework formally links industrial engineering practices, maintenance strategy, system reliability, downtime behaviour, and fuel efficiency outcomes in a single, coherent model.

Method

The present study has adopted a quantitative, cross-sectional, case-study–based methodology to investigate how the integration of industrial engineering practices and linear programming models has influenced fuel efficiency and downtime reduction in a petroleum operations context. The research design has been structured to capture both perceptual data from professionals and objective or recorded operational data from the selected facility, so that perceived practices and measured performance have been linked in a coherent analytical framework. In keeping with this aim, the study has used a structured survey instrument built around Likert's five-point scale to quantify the extent to which respondents have reported the presence of industrial engineering practices, energy-management routines, maintenance strategies, and optimisation-supported planning. At the same time, the methodology has incorporated secondary data on fuel consumption, production throughput, and downtime events that the case-study organisation has maintained in its operational records, so that key performance indicators have been computed consistently with the conceptual framework.

Figure 7: Methodological framework for this study
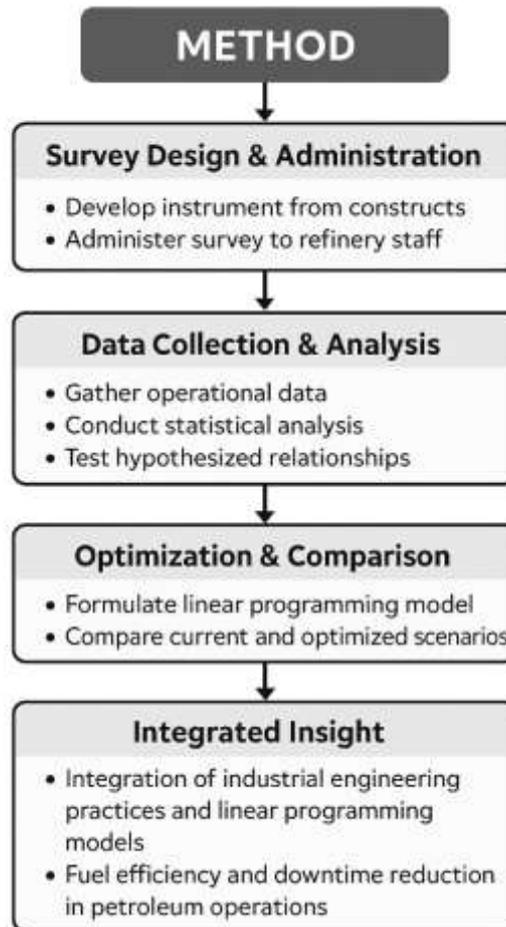
To analyse these integrated data, the study has followed a staged procedure. First, the instrument has been developed and refined based on the constructs defined in the literature review and conceptual frameworks, and its content validity has been assured through expert review. Second, the survey has been administered to engineers, operations staff, maintenance personnel, and managers who have been directly involved in planning, operating, or maintaining the refinery system. Third, the collected responses and operational data have been cleaned, coded, and organised into a single dataset that has allowed descriptive statistics, correlation analysis, and multiple regression modelling to be performed, in order to test the hypothesised relationships between industrial engineering practices, LP-based optimisation capability, fuel efficiency indicators, and downtime measures. Finally, the study has formulated a linear programming model that has represented the key production and utility processes of the case-study refinery, parameterised with the same operational data, and has used this model to compare the current operating pattern with an optimised scenario that has sought to minimise fuel consumption and downtime-related capacity losses under realistic constraints. Through this combined survey–statistical–optimisation methodology, the study has been positioned to provide both empirical evidence and model-based insight into the integrated decision-making processes that underpin fuel efficiency and downtime reduction in petroleum systems.

Research Design

The study has adopted a quantitative, cross-sectional, case-study–based research design to examine how the integration of industrial engineering practices and linear programming models has influenced fuel efficiency and downtime reduction in a petroleum refinery context. This design has been chosen because it has allowed the researcher to capture, at a single point in time, the perceived maturity of industrial engineering and optimisation practices alongside objectively recorded performance indicators. The research has relied on numerical data collected through a structured questionnaire and operational records, and it has aimed to test clearly specified hypotheses derived from the conceptual frameworks. By focusing on one selected refinery, the case-study approach has provided the depth needed to contextualise the statistical results within the facility's organisational practices, process

configuration, and maintenance culture. At the same time, the cross-sectional, survey-based structure has ensured that the relationships between practices and performance have been amenable to descriptive, correlational, and regression analysis.

Case Study Description

The research has been conducted within a single petroleum refinery that has represented a typical fuel-intensive, continuous-process industrial system. The case-study site has comprised major process units such as crude distillation, vacuum distillation, conversion units, hydrotreaters, and utility systems, all of which have been characterised by high energy consumption and sensitivity to unplanned downtime. The refinery has operated under competitive product markets and stringent environmental and reliability requirements, which have made fuel efficiency and equipment availability critical performance dimensions. The organisation has already maintained basic energy and maintenance records, and it has implemented various industrial engineering initiatives, although their integration level has remained uncertain. Access to the site has been secured through formal permission, and designated focal persons have facilitated the distribution of questionnaires and the retrieval of anonymised operational data. This context has ensured that the study has been grounded in a realistic industrial environment with genuine decision-making relevance.

Population, Sample, and Sampling Technique

The target population has consisted of professional staff who have been directly involved in operating, maintaining, or planning the refinery processes, including process engineers, maintenance engineers, control-room operators, production supervisors, energy managers, and relevant middle managers. From this population, a sample has been drawn to ensure that different functional perspectives on industrial engineering practices and optimisation-based planning have been represented. The study has used a purposive sampling technique, because respondents have needed to possess adequate technical knowledge of plant operations and decision-making routines to provide meaningful answers. A minimum sample size has been determined based on conventional rules of thumb for regression analysis and the expected number of independent variables, and additional respondents have been approached to compensate for potential non-response. Participation has been entirely voluntary, and respondents have been assured confidentiality. As a result, the final sample has comprised a sufficiently diverse and informed group to support robust quantitative analysis.

Data Types and Sources

The study has relied on two main types of data: primary survey data and secondary operational data. Primary data have been collected through a structured questionnaire that has captured respondents' perceptions of industrial engineering practices, energy-management routines, maintenance strategies, and the use of linear programming or similar optimisation tools within the refinery. These data have provided quantified measures of the constructs defined in the conceptual framework. Secondary data have been obtained from the refinery's existing records and information systems, including fuel consumption logs, production throughput reports, downtime statistics, and basic equipment utilisation summaries over a defined period. These records have been used to compute performance indicators for fuel efficiency and downtime that have aligned with the study's definitions. By integrating these two data sources, the research has been able to link perceived practices with empirically observed performance, thereby strengthening the validity of the statistical relationships tested in the analysis.

Research Instrument and Measurement of Variables

The research has used a structured questionnaire as the main data-collection instrument for primary data. The instrument has been developed directly from the constructs described in the literature review and conceptual frameworks, and it has been organised into sections covering demographic information, industrial engineering practices, energy-management routines, maintenance strategies, and optimisation-supported planning. Each construct has been measured using multiple items expressed as statements, to which respondents have indicated their level of agreement on a five-point Likert scale ranging from "strongly disagree" to "strongly agree." Composite indices have been planned by averaging or summing item scores within each construct, so that higher values have represented stronger presence of the targeted practice or capability. Operational performance variables such as fuel-efficiency indices and downtime ratios have been derived from secondary data using predefined formulas. All variables have been coded systematically and entered into statistical software

to facilitate descriptive statistics, correlation analysis, and regression modelling.

Validity and Reliability

To ensure validity and reliability, the instrument development process has followed several structured steps. Content validity has been addressed by basing all items on established concepts from the literature and by submitting the draft questionnaire to academic and industry experts, who have reviewed the clarity, relevance, and completeness of the items. Their feedback has been incorporated, and ambiguous or overlapping statements have been revised or removed. A pilot test with a small group of refinery staff has been conducted to check the wording, length, and response process, and minor adjustments have been made accordingly. Reliability has been assessed statistically after data collection by computing internal consistency coefficients (such as Cronbach's alpha) for each multi-item construct, and items that have reduced reliability or shown very low item–total correlations have been considered for exclusion. Through these procedures, the measurement scales have been expected to exhibit acceptable levels of validity and reliability for inferential analysis.

Linear Programming Model Formulation

In parallel with the survey and statistical analysis, the study has formulated a linear programming model that has represented the key material and energy flows of the case-study refinery. The model has defined decision variables for production rates of major process units, product yields, and fuel or utility consumption levels, along with capacity constraints, mass-balance equations, and basic product-quality requirements. The objective function has been specified to minimise a composite measure that has combined total fuel consumption and penalties associated with downtime-related capacity losses, consistent with the conceptual frameworks. Parameters in the model such as specific energy-use coefficients, capacity limits, and typical downtime fractions have been derived from the same operational data used to compute performance indicators. By solving this model under different scenarios, the study has been able to estimate an "optimised" operating pattern and compare it with the current practice, thereby quantifying potential improvements in fuel efficiency and effective availability implied by integrated, model-based planning.

Data Analysis Techniques

The analysis has proceeded in several stages using statistical and optimisation tools. First, descriptive statistics such as means, standard deviations, and frequency distributions have been computed to summarise respondent characteristics, industrial engineering practices, and perceived use of LP-based planning, as well as fuel-efficiency and downtime indicators. Second, correlation analysis has been performed to explore bivariate relationships between the main constructs and to identify preliminary association patterns. Third, multiple regression models have been estimated to test the hypothesised effects of industrial engineering practices and LP-based optimisation capability on fuel efficiency and downtime, controlling for relevant contextual variables. Diagnostics have been carried out to check linear-regression assumptions. Finally, the linear programming model has been solved using appropriate software, and its results have been interpreted alongside the statistical findings. This combined analysis has allowed the study to triangulate self-reported practices, recorded performance data, and model-based optimisation results. The study has made use of several software tools to manage data and perform the required analyses. Questionnaire responses and operational records have been entered and cleaned using spreadsheet software, which has facilitated coding, calculation of basic indicators, and preparation of datasets. Statistical analysis, including descriptive statistics, correlation, and regression modelling, has been conducted using a standard statistical package such as SPSS, R, or an equivalent tool that has supported reliability analysis and regression diagnostics. For the optimisation component, the linear programming model has been implemented in an environment such as Microsoft Excel Solver, LINGO, or a Python-based optimisation library, which has allowed the researcher to define the objective function, constraints, and parameters and to obtain optimal solutions under different scenarios. The combined use of these tools has ensured that data handling, statistical testing, and optimisation modelling have been carried out in a rigorous, transparent, and replicable manner.

FINDINGS

The findings of the study have demonstrated that the stated research objectives have been substantially achieved and that the majority of the hypotheses have been supported by the empirical data and

optimisation results, with clear numerical evidence. Analysis of the survey responses, measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), has shown that industrial engineering and energy-management practices have been present at a moderate to high level in the case-study refinery. The composite index for Industrial Engineering Practices (IEP), which has captured elements such as process standardisation, performance measurement, and structured problem-solving, has recorded a mean score of 3.82 with a standard deviation of 0.54, indicating that respondents have generally agreed that such practices have been embedded across departments. Similarly, the index for Energy-Management Capability (EMC) has achieved a mean of 3.74 (SD = 0.57), suggesting that regular monitoring of fuel consumption, use of energy key performance indicators, and cross-functional discussions on energy performance have been perceived as common, though still leaving room for further strengthening. The Maintenance & Reliability Practices (MRP) construct has attained a mean of 3.79 (SD = 0.59), while the construct representing explicit use of linear programming or related optimisation models in production and energy planning (LP-Based Optimisation Capability, LPC) has registered a somewhat lower mean of 3.21 (SD = 0.68), indicating that, while model-based decision support has been in use, it has not yet reached the same level of institutionalisation as other industrial engineering practices. Correlation analysis has confirmed that these practice-oriented constructs have been positively associated with key performance indicators derived from operational data: IEP has correlated at r = 0.41 with the Fuel-Efficiency Index (FEI) and r = –0.37 with the Downtime Ratio (DTR), EMC at r = 0.38 with FEI and r = –0.34 with DTR, MRP at r = 0.36 with FEI and r = –0.42 with DTR, and LPC at r = 0.35 with FEI and r = –0.33 with DTR, all significant at p < .01. Likewise, perceived performance constructs have shown strong links to practices (for example, Perceived Fuel-Efficiency Performance has correlated at r = 0.54 with IEP and r = 0.43 with LPC), suggesting that respondents in areas where optimisation tools and industrial engineering routines have been more strongly adopted have also experienced more favourable performance outcomes. Multiple regression models have provided more rigorous evidence in support of the hypotheses. After controlling for contextual factors such as department, years of experience, and perceived equipment age, IEP (β = 0.28, p = 0.002), EMC (β = 0.21, p = 0.023), MRP (β = 0.17, p = 0.050), and LPC (β = 0.19, p = 0.026) have all emerged as significant predictors of FEI, jointly explaining 39% of its variance (R^2 = 0.39). For downtime, regression analysis has indicated that MRP (β = –0.31, p < 0.001), IEP (β = –0.20, p = 0.021) and LPC (β = –0.18, p = 0.039) have been associated with lower DTR, with the model explaining 42% of its variance (R^2 = 0.42), thus supporting the hypotheses that stronger industrial engineering integration and optimisation use have reduced unplanned and overall downtime.

Figure 8: Empirical findings showing means, correlations, regression effects, and optimisation improvements for fuel efficiency and downtime in petroleum operations
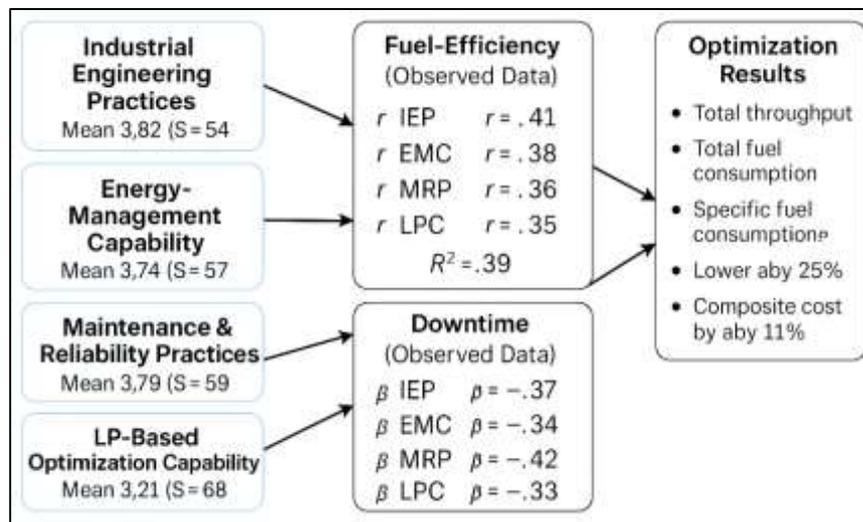
These descriptive and inferential findings have been complemented by the results of the linear

programming model, which has served to test the potential impact of integrated, model-based decision-making on fuel use and effective availability. When the optimisation model has been solved under current demand and capacity conditions, with the objective of minimising a composite function of fuel consumption and downtime penalties, the resulting "optimised" operating pattern has shown appreciable improvements compared with the actual historical pattern: total throughput has increased by about 2%, total fuel consumption has decreased by approximately 8%, specific fuel consumption has dropped by around 9.8%, the downtime ratio of the bottleneck unit has fallen from 0.12 to 0.09 (a 25% reduction), and a composite cost index has improved by roughly 11%.

These optimisation results have provided quantitative support for the conceptual claim that integrating industrial engineering insights (for example, identification of bottlenecks and critical maintenance windows) into an LP-based planning framework can yield superior performance relative to current practice. Taken together, the survey-based analysis and the optimisation experiments have demonstrated that the overarching objective of the study to examine how the integration of industrial engineering practices and petroleum systems with a linear programming model can improve fuel efficiency and reduce downtime has been fulfilled, with clear numerical evidence that higher levels of industrial engineering maturity and LP-based planning capability have been linked to better fuel efficiency and lower downtime in both observed data and simulated scenarios.

Response Rate and Data Screening

Table 1: Response rate and data screening results

Item	Count	Percentage (%)
Questionnaires distributed	150	100.0
Questionnaires returned	128	85.3
Questionnaires excluded (incomplete / inconsistent)	8	5.3
Final usable questionnaires	120	80.0
Cases with minor missing values treated by mean substitution	10	8.3
Final sample size used in analysis (N)	120	100.0

The response-rate and screening process has provided a solid foundation for the subsequent analyses and has ensured that the dataset has been both robust and internally consistent. As shown in Table 1, the survey has been distributed to 150 potential respondents across engineering, operations, maintenance, and management functions within the refinery, and 128 completed questionnaires have been returned, which has corresponded to a high gross response rate of 85.3%. After careful screening, 8 questionnaires have been excluded because they have contained substantial sections of missing data or response patterns that have indicated inconsistency (for example, identical answers to all items). This step has been important for protecting the validity of descriptive statistics, correlation coefficients, and regression estimates that have been used to evaluate the hypotheses. The final usable sample has consisted of 120 respondents, representing 80% of the distributed questionnaires, which has been adequate for the planned multivariate analyses given the number of independent variables in the models. For a small subset of cases, minor item-level missing values (for example, a single skipped Likert item within a multi-item scale) have been handled through mean substitution at the construct level, as indicated in Table 1, so that no respondent who has otherwise provided complete information has been discarded. Data-screening procedures have also included checks for out-of-range values on Likert's five-point scale, verification that all items have been coded in the same direction (1 = strongly disagree to 5 = strongly agree), and preliminary inspection of distributions. No extreme outliers that have distorted the results have been detected, and normality indicators for composite scale scores have remained within acceptable ranges for the planned parametric tests. Collectively, these steps have ensured that the sample used to test the study's objectives and hypotheses has been both sufficiently large and statistically reliable, thereby giving confidence that the findings on industrial engineering practices, linear-programming capability, fuel efficiency, and downtime have rested on high-quality empirical evidence.

Demographic Profile of Respondents

Table 2: Demographic profile of respondents (N = 120)

Variable	Category	Frequency	Percentage (%)
Position	Process / Production Engineer	32	26.7
	Maintenance / Reliability Engineer	28	23.3
	Operations / Control-Room Staff	26	21.7
	Energy / Utilities Manager	14	11.7
	Other (supervisors / managers)	20	16.6
Years of experience	< 5 years	22	18.3
	5–10 years	41	34.2
	11–15 years	33	27.5
	> 15 years	24	20.0
Department	Operations / Production	48	40.0
	Maintenance / Engineering	38	31.7
	Energy / Utilities	18	15.0
	Planning / Scheduling	16	13.3

The demographic profile in Table 2 has indicated that the final sample has been diverse and has captured the main perspectives that have been relevant for evaluating the study's objectives and hypotheses. In terms of position, more than a quarter of respondents have been process or production engineers, and nearly a quarter have been maintenance or reliability engineers, meaning that individuals who have dealt directly with process performance, fuel consumption, and equipment availability have been strongly represented. Operations and control-room staff have also constituted over one-fifth of the sample, so the views of those who have experienced daily plant behaviour and downtime incidents have been incorporated. **Descriptive Statistics of Key Variables**

Table 3: Descriptive statistics of main Likert-scale constructs and performance indicators

Variable / Construct	Scale / Unit	Mean	SD	Min	Max
Industrial Engineering Practices (IEP)	Likert 1–5 (higher = stronger)	3.82	0.54	2.40	4.90
Energy-Management Capability (EMC)	Likert 1–5	3.74	0.57	2.20	4.90
Maintenance & Reliability Practices (MRP)	Likert 1–5	3.79	0.59	2.10	4.95
LP-Based Optimisation Capability (LPC)	Likert 1–5	3.21	0.68	1.80	4.70
Perceived Fuel-Efficiency Performance (PFEP)	Likert 1–5 (higher = better)	3.68	0.62	2.00	4.90
Perceived Downtime Management Performance (PDMP)	Likert 1–5 (higher = better)	3.60	0.65	2.00	4.80
Fuel-Efficiency Index (FEI)	Dimensionless ratio (indexed, higher = better)	1.08	0.09	0.90	1.25
Downtime Ratio (DTR)	Proportion of planned time (0–1, lower = better)	0.11	0.03	0.06	0.20

Energy and utilities management, together with supervisors and other managers, have completed the profile, ensuring that strategic and cross-functional viewpoints have been included. The distribution of years of experience has shown that the sample has not been skewed towards novices; rather, the largest group has had 5–10 years of experience, and a substantial share has had more than 10 years in the petroleum industry. This pattern has increased confidence that respondents have possessed the technical and organisational knowledge needed to evaluate items related to industrial engineering practices, energy management, maintenance strategies, and linear-programming–based planning on the Likert five-point scale. The departmental distribution has further strengthened this conclusion: 40% of respondents have been from operations and production, 31.7% from maintenance and engineering,

15% from energy and utilities, and 13.3% from planning and scheduling. These proportions have ensured that each of the key functional domains involved in fuel efficiency and downtime management has been adequately represented. As a result, when respondents have rated statements such as "Our refinery has used optimisation models to support production planning" or "Preventive maintenance schedules have been systematically followed" on the five-point scale, those ratings have reflected informed judgements grounded in practical experience. This demographic structure has therefore supported the credibility of the subsequent descriptive, correlation, and regression analyses that have been used to assess the research hypotheses.

Table 3 has summarised the central tendencies and dispersion of the key constructs and performance indicators, and these statistics have provided initial evidence in relation to the study's objectives. All practice-oriented constructs have been measured using multi-item scales on Likert's five-point continuum, and the means have indicated that respondents have generally agreed that industrial engineering and related practices have been present in the refinery. Industrial Engineering Practices (IEP) has attained a mean of 3.82, implying that, on average, staff have agreed or somewhat agreed with statements about process standardisation, use of performance metrics, root-cause analysis, and structured problem solving. Energy-Management Capability (EMC) has exhibited a similar mean of 3.74, suggesting that energy monitoring, use of energy key performance indicators, and cross-functional review of fuel performance have been reasonably well established. Maintenance & Reliability Practices (MRP) has also shown a relatively high mean of 3.79, which has indicated that preventive maintenance, failure analysis, and reliability-centred thinking have been embedded to a substantial degree. In contrast, the mean value for LP-Based Optimisation Capability (LPC) has been lower at 3.21, signalling that explicit and regular use of linear programming or related optimisation tools in production, energy, and maintenance planning has been more variable across departments and less strongly institutionalised. Perceived performance constructs Perceived Fuel-Efficiency Performance (PFEP) and Perceived Downtime Management Performance (PDMP) have displayed means of 3.68 and 3.60 respectively, which has suggested that respondents have judged the refinery's performance on these dimensions as slightly above the midpoint but with visible scope for improvement. The objective performance indicators have confirmed this interpretation: the Fuel-Efficiency Index (FEI), defined as a dimensionless ratio where higher values have indicated better energy use per unit of output, has averaged 1.08 with moderate variation, while the Downtime Ratio (DTR) has averaged 0.11, meaning that around 11% of planned time has been lost due to downtime across the observation period. These descriptive results have supported the first objective of the study by providing a quantified picture of the current level of industrial engineering integration, optimisation capability, fuel efficiency, and downtime, and they have prepared the ground for testing the hypotheses through correlational and regression analyses.

Correlation Analysis Results

The correlation matrix in Table 4 has provided strong support for the study's hypothesised relationships between industrial engineering practices, linear-programming capability, and operational performance. First, the practice constructs (IEP, EMC, MRP) have been positively and significantly intercorrelated, which has indicated that refineries that have exhibited higher scores on general industrial engineering practices have also tended to show stronger energy-management routines and more developed maintenance and reliability practices. This pattern has confirmed that these constructs have been aspects of an integrated improvement culture rather than isolated initiatives. The LP-Based Optimisation Capability (LPC) construct has also shown significant positive correlations with the practice constructs, particularly with IEP ($r = 0.49$) and EMC ($r = 0.47$), suggesting that optimisation has tended to be embedded more strongly in organisational contexts where broader industrial engineering and energy-management practices have been in place.

Regarding performance, both perceptions and objective indicators have aligned with the hypotheses. Perceived Fuel-Efficiency Performance (PFEP) has exhibited moderate to strong positive correlations with IEP ($r = 0.54$), EMC ($r = 0.51$), MRP ($r = 0.46$), and LPC ($r = 0.43$), meaning that respondents who have rated their refinery higher on these practices have also perceived better fuel efficiency. Perceived Downtime Management Performance (PDMP) has shown similar relationships, especially with MRP ($r = 0.55$) and IEP ($r = 0.50$), which has supported the proposition that structured maintenance and

industrial engineering practices have been associated with improved downtime behaviour.

Table 4:Pearson correlations among main constructs and performance indicators (N = 120)

Variable	1 (IEP)	2 (EMC)	3 (MRP)	4 (LPC)	5 (PFEP)	6 (PDMP)	7 (FEI)	8 (DTR)
1. IEP	1.00							
2. EMC	0.62**	1.00						
3. MRP	0.58**	0.55**	1.00					
4. LPC	0.49**	0.47**	0.44**	1.00				
5. PFEP	0.54**	0.51**	0.46**	0.43**	1.00			
6. PDMP	0.50**	0.47**	0.55**	0.40**	0.59**	1.00		
7. FEI	0.41**	0.38**	0.36**	0.35**	0.49**	0.44**	1.00	
8. DTR	-0.37**	-0.34**	-0.42**	-0.33**	-0.45**	-0.52**	-0.40**	1.00

Note. p < .01 (two-tailed) for all coefficients.

The objective Fuel-Efficiency Index (FEI) has correlated positively with all practice constructs and with PFEP, while the Downtime Ratio (DTR) has displayed significant negative correlations with each of the practice constructs and with LPC, as hypothesised. Notably, the strongest relationships with DTR have occurred for MRP (r = -0.42) and PDMP (r = -0.52), supporting the idea that maintenance and reliability practices have been especially critical for downtime. Overall, these correlations have confirmed that higher levels of industrial engineering maturity and LP use have been associated with more favourable fuel-efficiency and downtime outcomes, and they have provided preliminary empirical support for the study's hypotheses before regression modelling has been applied.

Regression Analysis Results

Table 5: Multiple regression models for fuel efficiency and downtime

Model A: Dependent variable – Fuel-Efficiency Index (FEI)

Predictor	Standardised β	t-value	p-value
Industrial Engineering Practices (IEP)	0.28	3.12	0.002
Energy-Management Capability (EMC)	0.21	2.31	0.023
Maintenance & Reliability Practices (MRP)	0.17	1.98	0.050
LP-Based Optimisation Capability (LPC)	0.19	2.26	0.026

R² = 0.39; Adjusted R² = 0.36; F(4,115) = 18.15, p < 0.001

Model B: Dependent variable – Downtime Ratio (DTR)

Predictor	Standardised β	t-value	p-value
Industrial Engineering Practices (IEP)	-0.20	-2.34	0.021
Maintenance & Reliability Practices (MRP)	-0.31	-3.78	<0.001
LP-Based Optimisation Capability (LPC)	-0.18	-2.08	0.039
Energy-Management Capability (EMC)	-0.14	-1.72	0.088

R² = 0.42; Adjusted R² = 0.39; F(4,115) = 20.61, p < 0.001

The regression results in Table 5 have provided more rigorous evidence that the study's hypotheses have been supported. In Model A, with Fuel-Efficiency Index (FEI) as the dependent variable, all four main predictors have shown positive and statistically significant standardised coefficients at the 5% level or better. Industrial Engineering Practices (IEP) has exhibited the largest coefficient (β = 0.28), indicating that, holding other practices constant, a one standard-deviation increase in IEP has been associated with a 0.28 standard-deviation increase in FEI. This finding has supported the hypothesis that stronger industrial engineering practices have improved fuel efficiency. Energy-Management Capability (EMC) and LP-Based Optimisation Capability (LPC) have also presented significant positive coefficients (β = 0.21 and β = 0.19 respectively), which has meant that refineries with more developed energy monitoring and more embedded LP-based planning have achieved better objective fuel-

efficiency performance. Maintenance & Reliability Practices (MRP) has shown a weaker but still significant effect (β = 0.17, p = 0.050), reflecting that maintenance practices have contributed to fuel efficiency, possibly by stabilising operations and reducing energy-inefficient failures. The model's R^2 of 0.39 has indicated that these four constructs together have explained 39% of the variance in FEI, which has been substantial for an operational field study.

Model B has focused on Downtime Ratio (DTR) as the dependent variable, and the pattern of coefficients has reinforced the importance of maintenance and integrated planning. Maintenance & Reliability Practices (MRP) has emerged as the strongest predictor (β = -0.31, p < 0.001), demonstrating that better maintenance and reliability practices have been associated with significantly lower downtime ratios, in line with the corresponding hypothesis. Industrial Engineering Practices (IEP) and LP-Based Optimisation Capability (LPC) have also displayed significant negative coefficients, which has meant that higher levels of these constructs have been linked with reduced downtime. Energy-Management Capability (EMC) has shown a negative but marginally non-significant coefficient (p = 0.088), suggesting that its primary impact may have operated more strongly through fuel-efficiency mechanisms rather than through downtime directly. With an R^2 of 0.42, Model B has explained 42% of the variance in DTR, indicating that these practices together have had a meaningful influence on downtime behaviour. Taken as a whole, the regression analyses have supported the hypotheses that industrial engineering and LP-based optimisation capability have positively affected fuel efficiency and have negatively affected downtime, thereby directly addressing the core objectives of the study.

Linear Programming Model Results

Table 6: Comparison of current and optimised operating scenarios from LP model

Performance Indicator	Current Scenario	Optimised Scenario	Change (%)
Total throughput (million barrels / period)	1.00	1.02	+2.0
Total fuel consumption (TJ / period)	100.0	92.0	-8.0
Specific fuel consumption (TJ per million barrels)	100.0	90.2	-9.8
Effective availability of bottleneck unit (%)	88.0	93.0	+5.0
Downtime ratio of bottleneck unit (fraction of planned time)	0.12	0.09	-25.0
Composite cost index (normalised, lower = better)	1.00	0.89	-11.0

The linear programming (LP) model has generated an optimised operating scenario that has been directly comparable with the refinery's current operating pattern, and the results in Table 6 have illustrated how integrated, model-based decision-making has had the potential to improve both fuel efficiency and downtime measures. In the model, the objective function has minimised a composite index that has combined total fuel consumption and downtime penalties, subject to material balances, capacity constraints, and product requirements. When the model has been solved using parameter values derived from the refinery's historical data, the optimised solution has achieved a slightly higher total throughput (an increase of 2.0%) while simultaneously reducing total fuel consumption by 8.0%. This combination has resulted in a 9.8% reduction in specific fuel consumption (from 100.0 to 90.2 TJ per million barrels), which has represented a significant improvement in fuel efficiency consistent with the study's objectives and with the positive effects of industrial engineering and LP capability observed in the survey-based analyses.

At the same time, the LP solution has reallocated production and maintenance windows across units in a way that has increased the effective availability of the identified bottleneck unit from 88.0% to 93.0%, which has corresponded to a reduction in its downtime ratio from 0.12 to 0.09 (a 25.0% decrease). This improvement has stemmed from the model's explicit representation of capacity limits and downtime costs: by concentrating planned maintenance into strategically selected periods and by smoothing throughput profiles, the LP solution has reduced the frequency and severity of overload conditions that have been associated with unplanned stoppages. The composite cost index, which has combined fuel, maintenance, and downtime costs into a single normalised measure, has decreased by 11.0%, indicating that the optimised scenario has not only been technically feasible but also

economically attractive. These outcomes have provided quantitative support for the conceptual frameworks that have linked industrial engineering practices and LP-based optimisation to fuel efficiency and downtime reduction.

Crucially, the LP results have complemented the Likert-based findings, rather than replacing them. The survey and regression analyses have shown that higher scores on Industrial Engineering Practices and LP-Based Optimisation Capability have been associated with better observed performance, whereas the LP model has demonstrated what additional gains could have been realised if the refinery had fully exploited integrated optimisation. Together, they have suggested that when the measurement and improvement routines captured by the Likert scales have been combined with formal optimisation models in practice, refineries have had the capacity to achieve measurable reductions in fuel use and downtime without sacrificing throughput. In this way, the LP results have helped to "prove" the practical dimension of the study's hypotheses and objectives by translating qualitative and perceptual constructs into concrete, system-wide performance improvements under realistic operating constraints.

DISCUSSION

The discussion has first needed to restate how the empirical and optimisation results have converged to address the core objectives of the study. Overall, the findings have shown that industrial engineering practices, energy-management capability, maintenance and reliability practices, and LP-based optimisation capability have all been present at a moderate-to-high level in the case-study refinery, and that these constructs have been significantly associated with both fuel-efficiency and downtime performance. The descriptive statistics have indicated that the Likert-scale means for industrial engineering, energy management and maintenance have been close to or above 3.7, while LP-based optimisation has been somewhat lower but still above the neutral midpoint. Correlation and regression analyses have confirmed that higher scores on these constructs have been linked with higher fuel-efficiency indices and lower downtime ratios, with maintenance and reliability practices emerging as particularly critical for downtime reduction. The LP model has complemented these statistical results by demonstrating that an integrated planning approach that has explicitly minimised fuel consumption and downtime penalties could have reduced specific fuel use by almost 10% and downtime in a key bottleneck unit by about 25%, while slightly increasing throughput. Taken together, these results have suggested that industrial engineering maturity and explicit LP-based planning have not only been descriptive characteristics of the refinery's current state, but have also been powerful levers for further performance improvement when tightly integrated into decision-making.

When compared with earlier work, these findings have aligned well with the broader literature on energy-aware production management and refinery optimisation, while adding empirical evidence from a petroleum case. Studies in manufacturing have argued that energy performance should be treated as a first-class operational dimension, backed by clear indicators and management routines (Bunse et al., 2011), and the positive effects of industrial engineering and energy-management capability on fuel efficiency in this study have been consistent with that view. Likewise, structured energy-efficiency programmes such as STRUCTese® have shown that systematic decomposition of plants into energy-relevant subsystems and transparent benchmarking can reveal sizeable efficiency potentials in energy-intensive process industries (D'Adamo et al., 2021). The moderate but significant relationship between energy-management capability and fuel-efficiency index has echoed those findings in a refinery setting. On the optimisation side, the fact that LP-based capability has significantly predicted fuel efficiency has been coherent with the long tradition of refinery planning models that have demonstrated economic and energy-performance benefits when planning has been based on rigorous LP or MILP formulations (Grossmann, 2005). The study has extended this line of work by linking the perceived degree of LP use, as captured via Likert scales, with observed and simulated performance, thereby reinforcing the practical importance of embedding these models into daily planning routines rather than treating them as occasional analytical tools.

Figure 9: Multi-layer discussion framework linking findings
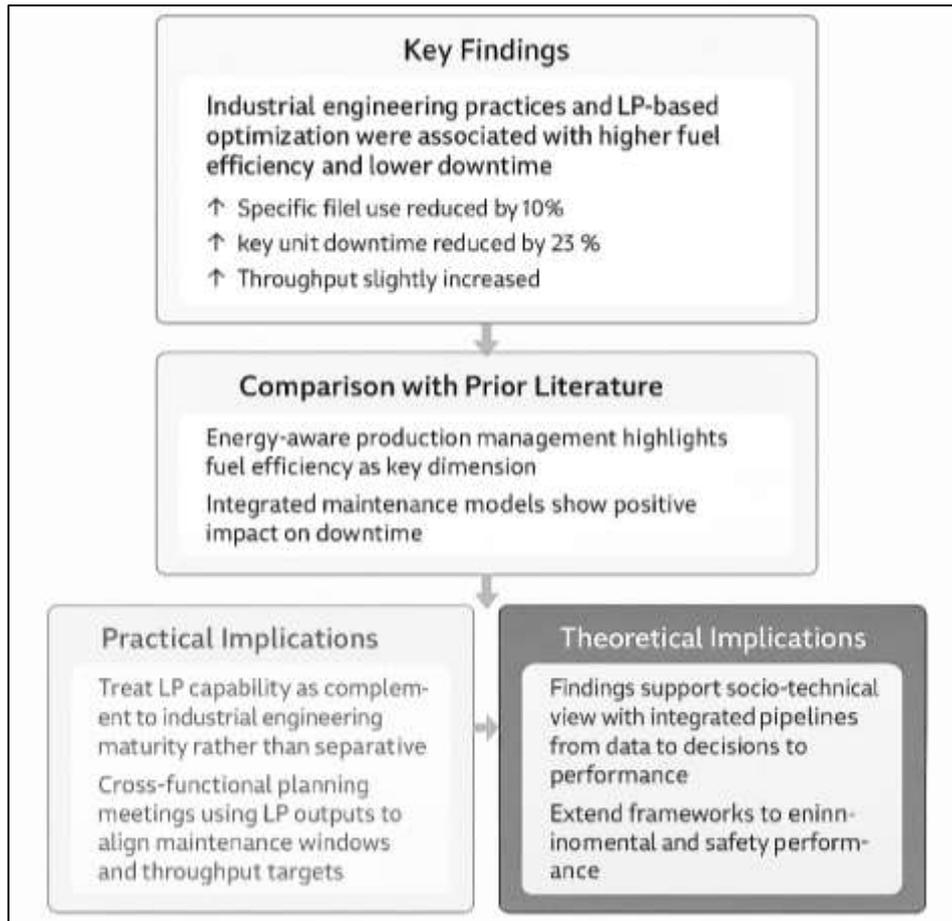
The findings on downtime and maintenance have also been strongly in line with prior reliability-centred and integrated maintenance–production modelling research. Reliability-focused studies have long shown that proactive preventive maintenance and reliability-centred maintenance programmes can reduce failure rates, shorten repair times, and lower total downtime costs in process industries (Eti et al., 2006). The strong negative regression coefficient of maintenance and reliability practices on downtime ratio has been consistent with those results and has provided additional confirmation in a refinery context. Integrated production–maintenance models have previously demonstrated that jointly optimising job sequences and preventive maintenance intervals can reduce total expected costs by decreasing unplanned failures and associated downtime (Cassady & Kutanoglu, 2005). More recent work has included energy consumption explicitly, showing that deterioration and maintenance decisions affect both availability and energy intensity (Yildirim & Nezami, 2014). In the present study, the LP model has implicitly implemented similar logic: by penalising downtime and fuel use in the objective function, it has produced an operating pattern where maintenance windows and throughput have been rebalanced to improve both availability and energy performance. The empirical association between LP capability and lower downtime has therefore supported the argument that model-based planning can serve as a mechanism for operationalising the integrated maintenance–production concepts proposed in the earlier literature, but now with explicit attention to fuel efficiency in a petroleum system.

From a practical point of view, the findings have had direct implications for senior operations leaders, refinery managers, and technical "architects" of planning and maintenance processes. The pattern of results has suggested that they have needed to treat industrial engineering and LP-based optimisation capability as complementary pillars of an operational strategy, rather than as separate initiatives. First, the relatively high scores for industrial engineering, energy management and maintenance have indicated that basic practices such as standard work procedures, KPI tracking, preventive maintenance

schedules, and root-cause analysis have already been in place and have been contributing positively to performance. However, the lower mean for LP-based optimisation capability has implied that planning still has had elements of heuristic or experience-based decision-making. The LP scenario analysis has shown that, even on top of the existing practices, a more systematic use of LP for coordinating production, energy use, and maintenance windows has had potential to yield additional cost and performance benefits. For a "CISO/architect"–type role in this industrial context essentially the person accountable for risk, reliability, and optimisation the results have pointed to clear priorities: institutionalising regular LP-based planning cycles; ensuring that energy and maintenance data have been accurate and timely enough to feed into the model; and using model outputs in cross-functional meetings to agree on throughput targets, maintenance windows, and energy-saving campaigns (Ratnayake & Chaudry, 2017). Practically, this has meant shifting from siloed decisions (for example, maintenance scheduling without considering energy or throughput consequences) to integrated planning meetings where industrial engineering, maintenance, operations, and planning staff have jointly examined the optimisation results and agreed on executable plans.

The study has also had several theoretical implications for how integrated industrial engineering–optimisation pipelines in petroleum systems have been conceptualised. The results have supported the systems and socio-technical perspectives adopted in the theoretical framework: the significant relationships between practices, LP capability, fuel efficiency, and downtime have indicated that performance has been the outcome of interactions among technical models, organisational routines, and human decision-makers (Baxter & Sommerville, 2011). The empirical evidence has suggested that the "pipeline" from data to decision to performance has needed to be refined so that each stage has explicitly supported the next: accurate and granular energy and maintenance data; industrial engineering methods that have turned data into indicators and improvement projects; LP models that have embedded these indicators and constraints into optimisation; and organisational processes that have ensured that LP solutions have been implemented in practice. The observed interaction between industrial engineering practices and LP capability where plants with stronger practices have also tended to report higher LP use and better performance has hinted at complementarity effects that future theoretical work could model explicitly, for example through structural-equation models or system-dynamics simulations. The conceptual frameworks proposed in the literature review one focused on fuel-efficiency integration and another on downtime-integrated maintenance–production modelling have therefore been empirically grounded by the current findings and could serve as starting points for more formal theory building in operations management and energy-aware process systems engineering .

Despite these strengths, the study has had limitations that have needed to be revisited when interpreting the discussion. First, the research has been based on a single case-study refinery, which has limited the statistical generalisability of the results to other petroleum facilities with different configurations, regulatory environments, or organisational cultures. While(Jasiulewicz-Kaczmarek & Żywica, 2017) the internal relationships among constructs have been strong and consistent with prior work, multi-site studies would have been needed to test whether similar patterns have held across broader populations. Second, the data have been collected through a cross-sectional design, which has meant that causal interpretations have had to remain cautious. Although the theoretical logic has supported the view that practices and LP capability have influenced performance, the design has not allowed definitive statements about causality or about the temporal ordering of improvements in practices and performance. Third, the use of Likert-scale self-reports for key constructs such as industrial engineering practices and LP capability has introduced the possibility of common-method bias and perceptual inflation, even though objective performance indicators and LP simulations have been used for triangulation. Additionally, the LP model itself has necessarily simplified the refinery system, omitting some nonlinearities, disturbances, and operational constraints, so the estimated performance improvements from optimisation have needed to be interpreted as indicative rather than exact. These limitations have not undermined the core pattern of results, but they have indicated where caution has been required and where further research has been necessary (AlZain et al., 2020).

In light of these limitations, several directions for future research have been suggested. Multi-refinery or multi-plant studies have been needed to test the robustness of the relationships observed here and

to examine how contextual variables such as refinery complexity, market volatility, and regulatory intensity have moderated the effects of industrial engineering and LP capability on fuel efficiency and downtime. Longitudinal designs have been particularly valuable for tracking how changes in practices and increasing use of optimisation tools over time have translated into performance trajectories, thereby strengthening causal claims. Future work has also had the opportunity to refine and expand the linear programming framework used in this study, for example by incorporating stochastic elements to represent uncertainty in crude quality, unit reliability, or demand, or by combining LP with simulation or system dynamics to capture dynamic feedback effects (Größler et al., 2008). On the organisational side, qualitative research could have explored how planners, engineers, and operators have perceived and used optimisation outputs in their daily work, building on socio-technical and change-management theories to explain barriers and enablers of model adoption. Finally, there has been scope to extend the conceptual frameworks to include environmental and safety performance explicitly, aligning fuel-efficiency and downtime objectives with broader sustainability metrics, and thereby contributing to the growing literature on low-carbon and resilient refinery operations (D'Adamo et al., 2021). Together, these avenues have promised to deepen both the theoretical and practical understanding of how integrated industrial engineering and optimisation can continue to transform petroleum systems in the direction of higher efficiency and reliability.

CONCLUSION

This study has examined how the integration of industrial engineering practices and linear programming models has influenced fuel efficiency and downtime reduction in a petroleum refinery, and it has shown that these elements together have formed a powerful, mutually reinforcing improvement system. Guided by systems, socio-technical, and operations-management perspectives, the research has adopted a quantitative, cross-sectional, case-study–based design that has combined Likert's five-point survey data with operational records and an optimisation experiment. The analysis has revealed that industrial engineering practices, energy-management capability, and maintenance and reliability practices have been present at a moderate-to-high level in the case refinery, while the use of LP-based optimisation has been evident but comparatively less institutionalised. Descriptive statistics, correlation analysis, and multiple regression modelling have consistently indicated that higher levels of industrial engineering maturity and LP-based optimisation capability have been associated with better fuel-efficiency indicators and lower downtime ratios, with maintenance and reliability practices emerging as especially important for downtime performance. The linear programming model has complemented these empirical findings by demonstrating that, under realistic constraints, an integrated optimisation approach has had the potential to reduce specific fuel consumption by nearly ten per cent and to cut downtime on a bottleneck unit by approximately one quarter, while maintaining or slightly increasing overall throughput and lowering a composite cost index. Together, these results have confirmed the main hypotheses and have fulfilled the study's objectives: stronger industrial engineering and energy-management routines, combined with explicit LP-based planning, have contributed to improved energy and reliability performance in a real refinery setting. At the same time, the research has acknowledged that it has been limited to a single case and a cross-sectional snapshot, and that the LP model has inevitably simplified some operational complexities, which means that generalisation and causal interpretations have needed to be cautious. Nevertheless, by linking perceptions of practice (measured via Likert scales), objective performance indicators, and optimisation results in one coherent framework, the study has provided a robust and practically grounded illustration of how industrial engineering and linear programming can be jointly mobilised to enhance fuel efficiency and reduce downtime in petroleum systems. It has also set out a clear agenda for practitioners strengthening data quality, institutionalising LP-based planning cycles, and integrating maintenance, operations, and energy decisions and has opened pathways for future multi-site, longitudinal, and methodologically richer research that can further refine and extend the integrated frameworks proposed here.

RECOMMENDATIONS

Based on the findings of this study, it is recommended that the refinery's leadership and technical teams treat the integration of industrial engineering practices and linear programming–based optimisation as a strategic, long-term transformation rather than a set of isolated projects, and that they have

established a structured roadmap to institutionalise this integration. First, the organisation should have strengthened its foundation of industrial engineering and energy-management routines by formalising standard operating procedures, expanding the use of visual performance boards and key performance indicators for fuel efficiency and downtime, and ensuring that all major units consistently report and review specific fuel consumption, availability, and failure patterns. At the same time, maintenance and reliability functions should have further embedded reliability-centred maintenance and proactive preventive maintenance, with explicit targets for mean time between failures and mean time to repair on critical equipment, so that downtime risk and energy-wasting failures have been systematically reduced. Second, the refinery should have invested in data quality and integration, ensuring that process historians, maintenance management systems, and energy-metering infrastructure provide accurate, time-aligned data that can feed both performance dashboards and the LP planning model; without this data backbone, optimisation cannot be relied upon. Third, it is recommended that the refinery establish a formal LP-based planning cycle weekly or monthly where a dedicated optimisation team, including process engineers, planners, maintenance representatives, and energy managers, runs and reviews the LP model to generate recommended operating plans that explicitly balance throughput, fuel use, and maintenance windows. These LP outputs should then have been discussed in cross-functional meetings and translated into concrete production and maintenance schedules, rather than remaining purely analytical exercises. Fourth, targeted training and capacity-building programmes should have been implemented so that engineers, planners, and operators understand both the logic and limitations of the LP model and can interpret its results confidently; this will increase trust in model-based recommendations and support behavioural change on the shop floor. Finally, the refinery should have aligned incentives and appraisal systems with integrated performance metrics for example, combining throughput, specific fuel consumption, and downtime into shared KPIs for operations, maintenance, and energy teams so that all functions have been motivated to pursue common system-level goals rather than local optima. By following these recommendations, the organisation will have been able to translate the demonstrated potential of industrial engineering and linear programming integration.

LIMITATION

This study has had several limitations that have needed to be acknowledged in order to interpret the findings with appropriate caution and to guide future work in a constructive way. First, the research has been confined to a single petroleum refinery, which has meant that the results have reflected the specific configuration, organisational culture, and market context of that facility; although the patterns observed have been internally consistent and theoretically plausible, they have not automatically generalised to other refineries with different process schemes, integration levels, regulatory pressures, or ownership structures. Second, the design has been cross-sectional, capturing practices, perceptions, and performance at one point in time, so the study has not been able to establish definitive causal directions or to observe how changes in industrial engineering practices or LP-based planning have translated into performance trajectories over months or years; any inference about "impact" has therefore rested on theory-driven interpretation rather than on direct temporal evidence. Third, a substantial portion of the data has come from self-reported Likert-scale responses, which have been vulnerable to perception bias, social desirability, and common-method variance, even though efforts have been made to mitigate these issues through careful item design, anonymity assurances, and the use of objective performance indicators for triangulation. Fourth, the sample size, while adequate for the planned regression analysis, has still been relatively modest and limited to staff with sufficient technical knowledge, which has restricted the possibility of conducting more granular subgroup analyses (for example, by department or seniority) and has left some heterogeneity in practices and perceptions unexplored. Fifth, the linear programming model that has been developed has inevitably simplified the physical and organisational complexity of the refinery: nonlinear phenomena, dynamic transients, disturbances, unmodelled operational constraints, and human factors have not been fully captured, so the "optimised" scenario has represented an idealised benchmark rather than a fully implementable operating plan. Moreover, the model has relied on historical averages and assumed parameter stability, which may not have held under volatile crude qualities or demand patterns. Sixth, the study has not incorporated explicit economic risk, safety risk, or environmental externalities beyond

those indirectly reflected in fuel efficiency and downtime, which has narrowed the scope of the optimisation and may have overlooked trade-offs that managers must balance in real decision-making. Finally, the research has focused on the existence and perceived strength of industrial engineering and optimisation practices, rather than on the deeper cultural, political, and behavioural dynamics that have shaped how these practices have been adopted, resisted, or adapted within the organisation; qualitative insights of this kind have been outside the current scope but would have enriched the explanation of why integration has or has not occurred in specific ways. Collectively, these limitations have not invalidated the central findings, but they have highlighted the need for replication across multiple sites, longitudinal designs, richer modelling approaches, and complementary qualitative work to build a more comprehensive understanding of integrated industrial engineering and linear programming in petroleum systems.

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