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MODERN WEB - BASED DECISION SUPPORT SYSTEM FOR OIL REFINERY WORKFLOW TRANSFORMATION WITH ECONOMIC ANALYSIS

Osamah Shihab Ahmed AL-NUAIMI

Master's Thesis

Supervisor

Prof. Dr. Osman Nuri UÇAN

İstanbul, 2024

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The thesis titled MODERN WEB - BASED DECISION SUPPORT SYSTEM FOR OIL REFINERY WORKFLOW TRANSFORMATION WITH ECONOMIC ANALYSIS prepared by OSAMAH SHIHAB AHMED AL-NUAIMI and submitted on 26/01/2024 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Osamah Shihab Ahmed AL-NUAIMI

Signature

DEDICATION

I dedicate this research study, to my dear parents, may God prolong their lives, to my dear family, to my supervisor, Dr. Osman Nuri, who spared no effort in helping me ,to all my friends and those who accompanied me during my studies

ABSTRACT

MODERN WEB - BASED DECISION SUPPORT SYSTEM FOR OIL REFINERY WORKFLOW TRANSFORMATION WITH ECONOMIC ANALYSIS

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The refinery industry operates within a dynamic and competitive environment, requiring decision-makers to navigate complex challenges and uncertainties. This project focused on the development of a sophisticated Decision Support System (DSS) using advanced technologies such as NET 6 and C#. The primary objective was to empower decision-makers in the refinery industry with a robust tool to analyze extensive datasets, gain valuable insights, and make informed strategic choices. The project followed a systematic development process, involving the transformation of traditional Excel-based models into an automated application. By harnessing the capabilities of NET 6 and C#, the DSS facilitated seamless integration with backend systems, efficient data processing, and complex calculations. The frontend of the DSS was built using ReactJS, resulting in a user-friendly and visually appealing interface. Decision-makers can effortlessly navigate through the system, visualize data, and analyze key metrics, enabling them to make data-driven decisions with confidence. The implementation of the DSS offers significant advantages to the refinery industry. It reduces dependency on manual processes, automates data analysis, and provides real-time access to critical information. Decision-makers can explore various scenarios, evaluate financial implications, and optimize resource allocation. By streamlining the decision-making process, the DSS saves time, enhances operational efficiency, and empowers decision-makers to stay ahead in the competitive refinery industry. This project

underscores the transformative potential of advanced technologies in leveraging data for informed decision-making, fostering a competitive edge in the refinery industry landscape.

Keywords: Oil, Decision Support System, Web-Based Decision, Economic Analysis, Decision Support System (DSS).

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ABBREVIATIONS

IEA	:	International Energy Agency
DSS	:	Decision Support System
AI	:	Artificial Intelligence
IOT	:	Internet of Things
UI	:	User Interface
UX	:	User Experience
MVC	:	Model-View-Controller
C#	:	C-Sharp
SQL	:	Structured Query Language

1. INTRODUCTION

1.1 BACKGROUND

The oil and gas industry has long been characterized by challenges and uncertainties. Factors such as geopolitical tensions, supply disruptions, and technological breakthroughs have historically had a profound impact on the sector. However, the advent of the COVID-19 pandemic in 2020 introduced a previously unseen and substantial degree of unpredictability to the market dynamics, especially concerning projections and forecasts for the 2020 to 2025 period [1][2]. This was particularly evident when the International Energy Agency (IEA), in its Oil 2020 report, highlighted a significant downturn in global oil demand. For the first time since the global economic crisis of 2009, there was a drop in demand, plummeting by 2.5 million barrels every day during the initial three months of 2020 [3]. Even though there was an observable rebound in demand in the latter half of the year, the overall demand for oil in 2020 still registered a decline, falling short by roughly 90,000 barrels per day when compared to the previous year 2019 [1].

In terms of projections and in their analytical assessment of the period spanning from 2019 to 2025, the IEA posits a rather optimistic outlook for global oil demand. The agency envisions an average annual growth of 950,000 barrels per day, culminating in a total increment of 5.7 million barrels per day by the end of the forecasted timeline. One of the primary drivers for this anticipated surge in demand is the robust recovery expected in 2021. This recovery is set to pave the way for a steady annual growth rate, averaging around 1 million barrels per day up until 2025 [3].

The industry's complexities are not just confined to the demand side. The supply side, specifically the global oil production capacity, also exhibits dynamic shifts. According to the IEA, during the same forecast period, the world's oil production capacity is poised to experience an increase of 5.9 million barrels per day. Breaking it down further, non-OPEC countries are projected to contribute a significant portion of this increase, accounting for an additional capacity of 4.5 million barrels per day. On the other hand, the OPEC nations are also set to bolster their production capacity, adding an estimated 1.4 million barrels per day in crude oil and natural gas capacities. This interplay of growing production capacities and the ever-evolving demand underscores the intricate and ever-shifting landscape that oil refineries, and by extension the entire oil and gas sector, navigate in [3].

1.1.1 Decision-Making in the Industry

In the intricate realm of the oil refining industry, decision-making encompasses a multifaceted spectrum of factors. These range from the technical intricacies of refining processes to the broader economic implications and the imperative considerations related to environmental sustainability [4]. Such decisions are far from being straightforward. They are, in fact, an amalgamation of diligent data scrutiny, the foresight to anticipate upcoming market and industry trends, and the application of strategic acumen.

a. Diving deeper into the decision-making landscape, the initial step revolves around the acquisition of crude oil. Here, refineries grapple with determinants such as the intrinsic quality of the crude, its procurement costs, and its accessibility in the market. Parallelly, the industry is also acutely aware of the role geopolitics plays, especially in potentially jeopardizing the seamless supply of crude oil.
b. Once the crude oil is secured, the focus pivots to refining decisions. These decisions are fundamentally technical by nature. Based on the characteristics of the procured crude and the spectrum of output products envisioned, refineries have the arduous task of fine-tuning and optimizing refining processes. This optimization is paramount, aiming to derive the utmost efficiency and yield.
c. A pivotal component in the refining journey is the rigorous commitment to quality. This goes beyond merely producing; it's about producing right. Refineries incessantly engage in meticulous quality assurance practices, ensuring that their outputs align impeccably with established quality benchmarks. This often necessitates frequent evaluations and iterative adjustments within the refining processes.
d. The journey of crude oil doesn't end with refining; it extends to the logistical challenges encompassing transportation and storage of both the raw and refined products. Here, the decision-making lens focuses on cost efficiency, timely deliveries, and ensuring the safety of operations.
e. Environmental stewardship holds significant prominence in the oil refining industry's decision-making matrix [4]. With stringent local and international environmental legislations in play, refineries are perpetually on their toes, monitoring, managing, and mitigating their environmental footprint.
f. Stepping into the domain of strategic imperatives, refineries find themselves in the midst of decisions orbiting market demand nuances and intricate pricing dynamics [5].

This entails accurate demand forecasting for a myriad of refined products and calibrating operational modalities to align with these forecasts. Pricing verdicts, meanwhile, become a balancing act – harmonizing crude acquisition costs, refining operational expenditures, competitive market rates, and the ever-fluctuating market demand.

This labyrinth of decisions brings with it a colossal amount of data [5]. And with the escalating complexity of these decisions coupled with burgeoning data volumes, traditional computational tools like Excel are increasingly being deemed insufficient. The pressing demand now veers towards more advanced, adept tools capable of navigating these intricacies with finesse, amplifying both the efficiency and precision of decisions in the oil refining milieu [5]. As we progress further into this study, we will embark on a detailed exploration of a cutting-edge web-based decision support system (DSS). This DSS promises to be a solution tailored to surmount these industry challenges [2].

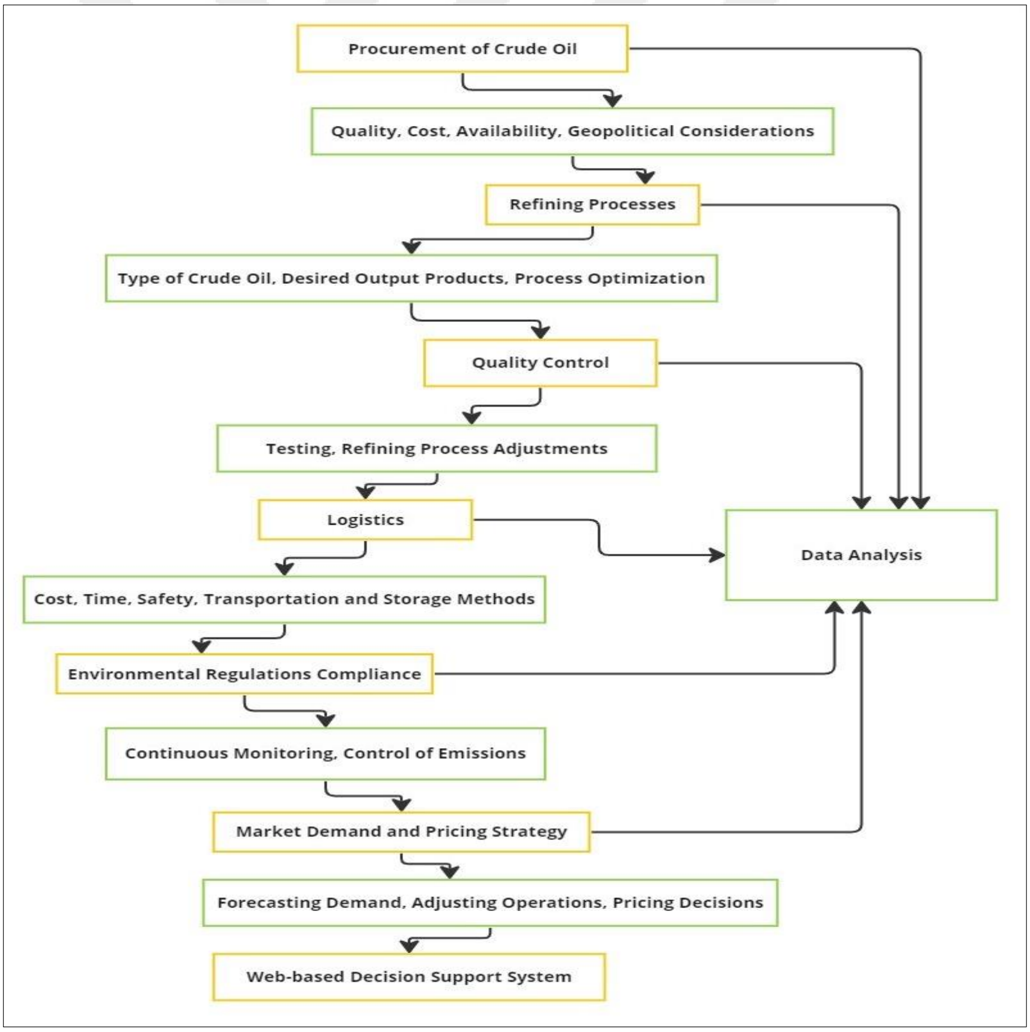


Figure 1.1: Decision Making Process.

1.1.2 Role of Data in Decision-Making

Within the intricate confines of the oil refinery industry, data has emerged as an indispensable cornerstone driving decision-making processes. The industry's transformation, fuelled by the tidal waves of digitalization and the introduction of the Industrial Internet of Things (IoT), has been nothing short of revolutionary. With these technological advancements, the realm of data in oil refining has expanded both in terms of volume and diversity. As a result, a vast reservoir of data now sprawls across the industry, acting as a treasure trove of insights. When harnessed judiciously, this data has the potential to not just refine decision-making contours but also catalyze heightened operational efficiency and boost profit margins [6].

To comprehend the scope and depth of data in the oil refinery sector, it's essential to delineate its origins. One of the primary sources of data emanates from an intricate web of sensors meticulously positioned throughout the refinery infrastructure. These sensors, operating in real-time, continually monitor and relay information on a plethora of parameters: from temperature fluctuations and pressure dynamics to flow velocities and the detailed chemical make-up of substances. This granular data is indispensable for the precise monitoring and adept control of the multifaceted refining operations. Additionally, the industry also finds itself inundated with market-centric data. This includes data vectors such as fluctuating oil prices, nuanced demand projections, and a spectrum of economic indicators. Each of these data fragments plays a pivotal role in sculpting strategic decisions for the industry.

As time has unfurled, a discernible shift towards a data-centric ethos is evident within the industry. Today, data isn't merely an adjunct; it's at the epicenter of decision-making in oil refining. Spanning the spectrum from technical intricacies to overarching strategic considerations, data's influence is omnipresent. On the granular technical front, data aids in refining optimization, facilitates precise equipment management, underpins rigorous quality assurance mechanisms, and ensures strict adherence to environmental mandates. Meanwhile, on the strategic canvas, it guides pivotal decisions surrounding crude procurement, the ideal product blend, nuanced pricing strategies, and investment trajectories [7].

However, while the importance of data is universally acknowledged, the task of adeptly managing and deploying this vast data ocean remains a formidable challenge. The entire data lifecycle, from its precise acquisition and secure archival to its adept processing and insightful analysis, is rife with complexities [6]. Furthermore, with the burgeoning data volumes and their inherent intricacies, traditional computational frameworks like Excel are increasingly rendered obsolete, thereby necessitating more sophisticated tools and approaches.

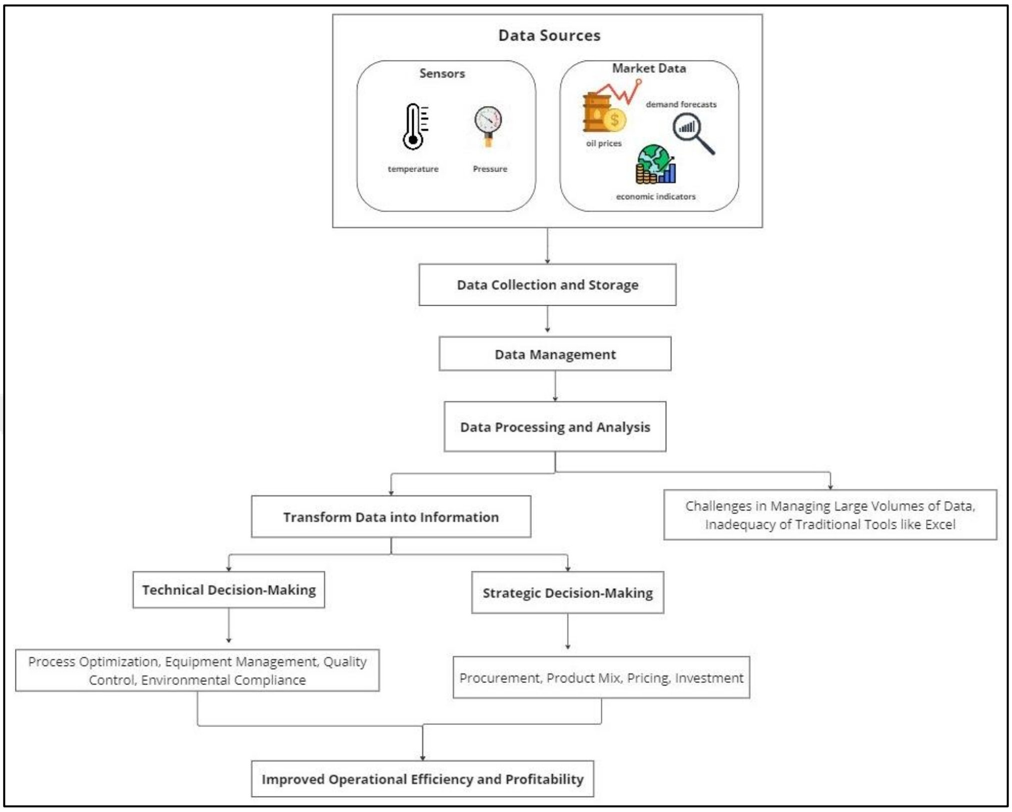


Figure 1.2: Data in Decision Making.

1.2 PROBLEM STATEMENT

The oil refining industry stands as one of the most data-intensive sectors, characterized by complex operations and strategic decision-making processes [8]. The industry deals with a broad range of decisions encompassing areas such as crude oil procurement, refining process optimization, quality control, compliance with environmental regulations, logistics, and market demand and pricing [5].

Traditionally, these decisions have been supported by tools like Microsoft Excel, offering data management, basic analysis capabilities, and a user-friendly interface. However, as the industry advances and becomes more digitalized and data-driven, these traditional tools are increasingly proving inadequate. Excel's limitations emerge in the face of growing data volumes, the complexity of analytics, collaboration needs, and error susceptibility. Its inability to efficiently handle large datasets, facilitate seamless collaboration, and provide advanced analytics, combined with a high potential for errors, significantly hampers its effectiveness as a decision support tool in the modern oil refinery industry [9].

These shortcomings underline the critical need for a more robust, scalable, and sophisticated DSS. The adoption of such a system can facilitate improved data management, enable advanced analytics, support effective collaboration, reduce error propensity, and ultimately drive better decision-making processes. However, transitioning from traditional tools to modern DSSs presents its own set of challenges, including the need for considerable initial investment, ensuring data security and privacy, and overcoming resistance to change among employees.

1.3 RESEARCH OBJECTIVES

This study aims to accomplish the following objectives:

a. Design a Web-based DSS: To develop a comprehensive design for a web-based DSS tailored to meet the specific needs of the oil refinery industry. This includes system architecture, data management modules, user interface, and functionalities that address the limitations of traditional tools like Excel.
b. Implement the System: To execute the practical implementation of the designed system, ensuring it provides real-time access to data, facilitates collaboration among multiple users, and is scalable to handle large volumes of data generated in the industry.
c. Advanced Analytics Capabilities: To incorporate advanced analytics capabilities within the system, enabling complex data analysis beyond the capabilities of traditional tools. This could include advanced statistical analysis, predictive modelling, machine learning algorithms, and data visualization features to aid decision-making processes.
d. Economic Analysis Feature: To integrate a feature for economic analysis within the system, enabling users to assess the economic viability of decisions over long-term periods (20-30 years). This should include forecasting, cost-benefit analysis, return on investment calculations, and other economic metrics important in the decision-making process.
e. Test and Evaluate the System: To perform rigorous testing and evaluation of the implemented system, ensuring it meets the industry's needs and enhances decision-making efficiency, workflow management, and profitability.

f. User Training and Acceptance: To develop a user training program for the system to ensure its successful adoption and usage in the industry. This will also involve analyzing user feedback to measure acceptance and refine the system as necessary.

By accomplishing these objectives, the study aims to bring significant transformation in the way the oil refinery industry manages its workflows and makes decisions, ushering in greater efficiency and profitability.

1.4 RESEARCH SIGNIFICANCE

This study bears significant implications for the oil refinery industry, particularly in the context of its transition towards a more digital, data-driven operational environment. Here are some key reasons why this study is significant:

a. Improving Decision-making Efficiency: By designing and implementing a web-based DSS, this study aims to enhance the decision-making efficiency in the oil refinery industry. The advanced analytics capabilities of the proposed system can provide deeper insights into data, aiding in better and faster decisions.
b. Enhancing Workflow Management: The study is significant in transforming the traditional workflow management in oil refineries. With real-time access to data and seamless collaboration features, the proposed system can streamline workflows, reduce bottlenecks, and enhance operational efficiency.
c. Economic Analysis: The inclusion of economic analysis features in the system adds to the study's significance. It provides a means for the industry to perform long-term economic viability assessments, helping in strategic decision-making related to investments, pricing, procurement, and more.
d. Increasing Profitability: By improving decision-making and workflow efficiency, the proposed system can contribute to increasing the profitability of oil refineries. Better decisions can lead to cost savings, increased output, and higher product quality, all contributing to improved profitability.
e. Leading Industry Transformation: Lastly, the study is significant as it paves the way for digital transformation in the oil refinery industry. It not only provides a blueprint for a web-based DSS but also offers insights into the challenges and strategies related to its implementation.

1.5 THE THESIS STRUCTURE

Chapter 2: Decision Support System in the Literature. This section reviews the existing literature on Decision Support Systems (DSS), focusing on their history, components, working, benefits, and uses. It also discusses the application of DSS in the oil refinery industry. Chapter 3: System Design and Development Process. This section outlines the objective of the project, the system requirements (both functional and non-functional), and the design and architecture of the system. It also discusses the user interface design, user flows, and calculation formulas. Chapter 4: Interfaces Design. This section delves into the development and coding of the system, including the use of the Model-View-Controller (MVC) pattern and the justification for the chosen frameworks and technology. It showcases the user interface, including the creation of the input sheet and the output sheet, and the design of the dashboard and calculation sheet. Chapter 5: Conclusion. This final section summarizes the research, discusses its implications, and may suggest areas for further research.

2. DECISION SUPPORT SYSTEM IN THE LITERATURE

2.1 DECISION SUPPORT SYSTEMS (DSS)

A DSS is a specialized information system that supports business and organizational decision-making activities [10]. This sophisticated system is a flexible, interactive software designed to produce comprehensible data, using raw data inputs and business models, to aid decision-makers in their tasks [11].

DSS serve at the intersection of information technology and management decision-making, providing data processing capacity to enhance the quality of managerial decisions [12]. They are typically used in scenarios where decisions are not straightforward and require the analysis of a variety of factors. These systems do not replace the human decision-making process, but rather provide a robust toolset that assists decision-makers in understanding the implications of various courses of action.

The main components of a DSS include a data management system, a model management system, and a user interface [13][14]. The data management system stores and maintains the information that is used by the DSS [15]. The model management system includes financial, statistical, management science or other quantitative models that provide the system's analytical capabilities [16]. The user interface is the means by which users interact with the DSS [17].

In essence, a DSS empowers businesses and organizations to make informed decisions by providing a framework for gathering, interpreting, and presenting data. By assisting in the analysis of business data, DSS help decision-makers to identify and solve problems, and to evaluate potential business strategies.

2.1.1 History of DSS

The roots of DSS can be traced back to the 1960s with the emergence of management information systems (MIS) [18]. These early systems focused on delivering structured, routine reports from transactional data to managers.

In the 1970s, the concept of DSS was formally introduced by Peter Keen and Charles Stabell. They described DSS as an interactive computer-based system aimed at helping decision-makers solve complex problems [19]. At that time, DSS mainly used simple databases and model management software.

The 1980s saw a shift from mainframe-based DSS to personal computer systems. As databases grew larger and more complex, the term 'Executive Information Systems' (EIS) was coined [20]. These systems offered executives a quick and easy way to get pertinent, summarized information directly from the computer system.

The 1990s marked the arrival of data warehouses and Online Analytical Processing (OLAP) tools, enabling more sophisticated analyses [21][22]. During this period, DSS began to incorporate artificial intelligence (AI) techniques such as expert systems and machine learning algorithms to improve decision-making capabilities.

The 2000s brought the concept of Business Intelligence (BI), which extended DSS capabilities to include predictive analytics, performance benchmarking, and data visualization [22]. Web-based DSS also became popular, allowing remote access and collaboration among decision-makers.

In recent years, the growth of big data, AI, machine learning, and advanced analytics has further transformed the landscape of DSS. Today, DSS not only help in decision-making but also predict future trends, perform complex analytics, and provide insights into the data. As a result, modern DSS are more intelligent, versatile, and user-friendly than ever before.

Moving forward, it's expected that emerging technologies such as cloud computing, Internet of Things (IoT), and advanced AI will continue to shape the future of DSS [57], further enhancing their capabilities and applications in decision-making.

2.1.2 Components of Decision Support System

A DSS is a tool professionals use to help them make informed and intelligent business decisions. DSSs can have various functions and focuses depending on the industries and the professionals employing them [23].

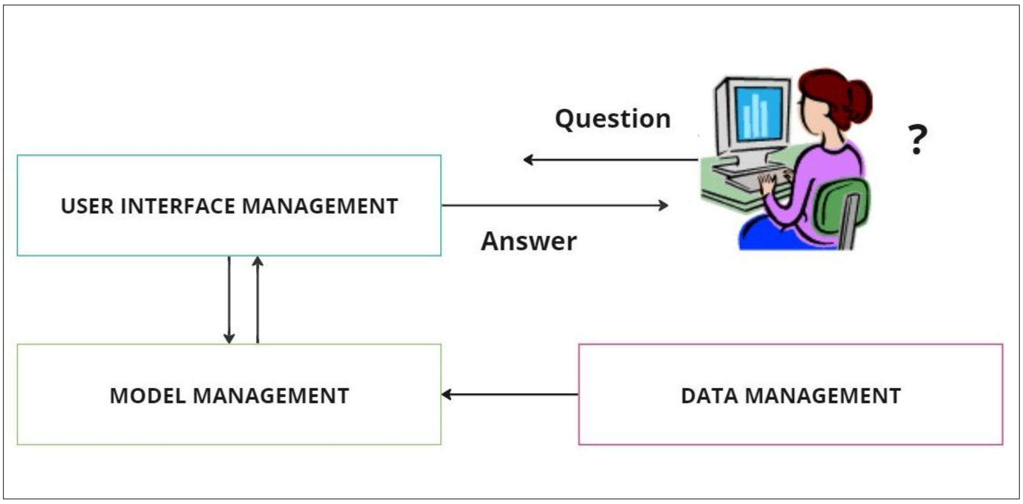


Figure 2.1: Components of Decision Support System.

2.1.2.1 Data management

The data management component is one of the most critical parts of a DSS [14]. It encompasses everything related to data handling within the system, including data collection, organization, storage, retrieval, and updating.

Data forms the foundational layer of any DSS. It serves as the basis for all analysis, modelling, and decision-making activities within the system [58]. By processing this data, the DSS can generate useful insights, identify patterns, make predictions, and provide recommendations to help decision-makers.

The data in a DSS can be collected from a wide variety of sources, including internal sources such as company databases, and external sources like current market trends or competitor data [24]. This data is then compiled, processed, and presented in a way that facilitates understanding and analysis.

In a DSS, data is typically organized into a data warehouse or a data mart. These systems store data in a format that facilitates easy retrieval, update, and analysis [25][26]. The data is often structured in a way that reflects the business processes and decision-making needs of the organization.

Data storage involves keeping data in a form and manner that it can be used when needed. Effective data storage solutions ensure data integrity, security, and accessibility. On the other hand, data retrieval is the process of extracting the stored data for analysis and decision-making. Efficient data retrieval mechanisms are crucial for the timely availability of data [26].

Data updating refers to the process of maintaining the currency and accuracy of data. This involves adding new data, modifying existing data, and deleting obsolete data. Regular data updating is crucial for ensuring that the DSS operates on the most recent and accurate data, thereby leading to more reliable and valid decision-making [27].

2.1.2.2 Model management

Model Management in a DSS is a critical component that handles data manipulation and analysis via various mathematical and statistical models [14]. It is this aspect of the DSS that provides the capacity for comprehensive data evaluation, predictive modelling, simulation, and optimization.

The role and significance of Model Management within a DSS are multifaceted. Fundamentally, this is where the actual 'intelligence' of the DSS is activated. When different models are applied to the data, the DSS can produce insights, make predictions, identify patterns, evaluate scenarios, and offer decision recommendations [59]. The outcomes from the model management component form the bedrock for decision-making in the system.

There is an array of models that can be utilized within a DSS, each depending on specific decision-making needs. These can range from statistical models for data analysis and trend identification to predictive models for forecasting [28], as well as simulation models for scenario evaluation and optimization models for discovering optimal solutions.

Building a model for a DSS is a meticulous process that involves clearly defining the problem, identifying the relevant variables, and selecting the most fitting modelling technique [60]. Factors such as the nature of the problem, the type of available data, the desired accuracy level, and the computational resources at disposal will influence the choice of model.

Following the creation of the model, it is implemented within the DSS to analyze the data. The results generated by the model are then evaluated for their validity, reliability, and usefulness for decision-making. This process might involve comparing the model's predictions with actual outcomes, assessing how well the model fits the data, and gauging the sensitivity of the model to changes in parameters or inputs.

Just as data needs to be regularly maintained and updated, so too do the models within a DSS. This might involve refining the model parameters based on new data, modifying the model to accommodate changes in the decision-making environment, or even replacing the model entirely with a more suitable one if necessary.

2.1.2.3 User interface

The User Interface (UI) component in a DSS serves as the interactive bridge between the system and its users, allowing for the flow of inputs and outputs [14]. Its design and functionality are crucial in ensuring effective communication, ease of use, and user satisfaction [29].

A well-designed UI makes the complex workings of a DSS accessible and straightforward to the users, reducing cognitive load and allowing them to focus on decision-making. It is the medium through which users can feed data into the system, define and adjust parameters, manipulate models, initiate analyses, and interpret results [30].

In the user interface, data and results are often presented in a visual, easy-to-understand format, making use of tables, charts, graphs, maps, and other visualizations. These representations allow users to quickly grasp patterns, trends, outliers, and key insights, enhancing their decision-making process [30].

Additionally, UI also includes controls for querying the system, launching different analyses, modifying the system's settings, and managing the data and models. The aim is to give users an easy-to-navigate and intuitive environment where they can use the DSS effectively, even without deep technical knowledge.

The design of the user interface should consider the users' needs, their technical proficiency, their role in decision-making, and the context of use. It should be user-friendly, clear, consistent, and responsive. Moreover, modern DSS often incorporate principles of User Experience (UX) design, ensuring not just the usability of the system but also the overall experience of the user [31].

2.1.3 Working of Decision Support System

A DSS is a powerful tool that assists organizations by analyzing and synthesizing vast amounts of data, thereby enabling the production of detailed reports and insights. These insights can be crucial for various applications, such as projecting revenue, managing inventory, or forecasting sales trends [32]. The DSS stands out for its capacity to integrate multiple variables, thereby generating a range of potential outcomes. This functionality is rooted in the organization's historical data and the analysis of current inputs [33].

For instance, in the context of launching a new marketing campaign, a DSS can play a pivotal role. It can consider various factors, including historical sales data, current market trends, and the costs associated with the campaign. Utilizing these inputs, the system is capable of forecasting potential increases in sales resulting from the campaign under diverse scenarios. This predictive capability is what makes a DSS an invaluable asset for decision-makers.

By enabling the forecast of decision outcomes before their implementation, a DSS provides a significant advantage. Decision-makers are equipped to make informed choices, backed by comprehensive data analysis. This not only minimizes risks but also enhances the likelihood of achieving strategic objectives. With a DSS, organizations can navigate complex decision-making processes more efficiently, aligning their actions with data-driven insights for better outcomes.

2.1.4 Benefits and Uses of DSS

DSS bring about a transformation in decision-making processes across industries by enhancing decision-making capabilities. The improved decision-making is facilitated by the DSS's ability to provide evidence-based insights, drawn from extensive data analyses. These systems allow decision-makers to visualize various scenarios and comprehend the potential impacts of their decisions [34]. Such detailed insight and data-backed decisions invariably lead to more accurate and effective choices, which substantially reduce the guesswork and uncertainty in the decision-making process.

Operational efficiency is another significant advantage conferred by DSS. The automation of complex data analyses and real-time insights provided by DSS can drastically improve operational efficiency within an organization [35]. Tasks that would otherwise require significant time and resources for data compilation and analysis can be accomplished swiftly and effortlessly, freeing up resources for other tasks and optimizing the overall workflow.

The contribution of DSS to increased profitability cannot be overstated. Optimized decision-making processes, facilitated by DSS, often result in strategies that maximize revenue, minimize costs, and improve resource allocation. DSS can also enhance customer satisfaction by helping organizations make data-driven decisions that cater to their customers' needs and preferences. Such operational enhancements and strategic choices can cumulatively lead to increased profitability.

Another pivotal role of DSS is in the sphere of risk management. DSS can help organizations identify potential risks by analyzing historical and real-time data. Once potential risks are identified, the DSS can assess their possible impacts, enabling organizations to develop strategies to mitigate these risks proactively. This feature of DSS is particularly important in industries where decisions could have significant financial or operational consequences.

Strategic planning is yet another area where DSS can make a considerable contribution. With their ability to provide insights into market trends, competitive dynamics, customer behaviour, and other key factors, DSS play an instrumental role in shaping an organization's strategic goals and plans. These insights, derived from the analysis of extensive data, can help organizations anticipate future trends and make strategic choices that ensure their growth and competitiveness in the market.

Finally, the high degree of customization that DSS offer is one of their most significant advantages. DSS can be tailored to meet the specific needs of an organization or industry. This versatility makes them a valuable tool that can be leveraged across a wide range of contexts, from healthcare to retail to the oil refining industry. This aspect of DSS ensures that their benefits can be reaped by organizations of all sizes and from all sectors. These benefits and uses of DSSs make them an indispensable tool in the contemporary business environment. By embracing DSS, organizations can ensure that they stay competitive, profitable, and prepared for the challenges of the future.

The versatility and adaptability of DSS make them particularly valuable in today’s rapidly evolving business landscape. In an era marked by data proliferation and complex decision-making scenarios, DSS stand out for their ability to handle diverse data sets and provide nuanced analyses. They are not just tools for processing large volumes of data; they also bring a level of sophistication to data interpretation, making complex patterns and trends comprehensible to decision-makers. This aspect of DSS is crucial, especially when dealing with multifaceted challenges that require a balance between short-term gains and long-term strategic goals. Furthermore, DSSs facilitate collaborative decision-making by providing a common platform where insights from various departments can be integrated and analyzed cohesively. This holistic approach ensures that decisions are not made in silos but are the result of cross-functional insights and expertise, leading to more robust and sustainable business strategies. By harnessing the power of DSS, organizations not only enhance their immediate operational and strategic decisions but also lay down a foundation for continual learning and adaptation. This dynamic approach, powered by DSS, enables organizations to remain agile and responsive to market changes, regulatory shifts, and evolving customer expectations. In essence, DSSs embody a transformative influence in the realm of business decision-making, offering a blend of precision, agility, and foresight that is indispensable in navigating the complexities of the modern business environment.

2.2 DSS IN THE CONTEXT OF THE OIL REFINERY INDUSTRY

DSS have significant relevance in the oil refinery industry, playing a critical role in optimizing various processes and activities [36]. Oil refineries are complex entities dealing with myriad variables, from fluctuating crude oil prices and refining costs to unpredictable demand patterns and stringent environmental regulations. Making informed decisions in such a complex and dynamic environment requires comprehensive data analysis, which is where DSS come in [37].

DSS can aid in several key decision-making processes in the oil refinery industry. For instance, they can help in forecasting the demand for different types of petroleum products based on historical data and market trends. This information can assist in planning production schedules and optimizing resource allocation. The accuracy of these forecasts can significantly impact the profitability of oil refineries, making DSS a crucial tool in these contexts. The allocation of crude oil to different processing units within the refinery is another area where DSS can be highly beneficial [38]. DSS can analyze the composition of crude oil and the processing capabilities of various units to determine the most efficient allocation. This can result in optimized production and minimized wastage.

Additionally, DSS can contribute to better risk management within oil refineries. They can help identify potential operational risks, assess their possible impacts, and recommend preventative actions [31]. For instance, DSS can monitor equipment performance data to predict possible failures and suggest timely maintenance [39], thus reducing the likelihood of costly downtime and accidents.

Furthermore, DSS can assist in strategic decision-making related to long-term investments and growth. For example, they can provide insights into market trends and forecast future demand, informing decisions about capacity expansion or the development of new refineries [40].

This study collates the latest structural attributes and crucial determinants of crude oil pricing based on preceding landmark findings [41]. To initiate, a novel dynamic Bayesian structural time series model (DBSTS) [61], has been developed for scrutinizing oil prices. Notably, Google trend data has been incorporated as an index to assess the influence of search data on oil pricing. Following this, the spike and slab technique has been leveraged to choose core determinants. Eventually, to predict oil prices, the Bayesian model average (BMA) [62], has been utilized. Findings from the study validate that global crude oil supply and demand and financial markets continue to be key drivers of oil prices. Additionally, it is evident that Google trend data to an extent mirrors fluctuations in crude oil prices. Moreover, while the influence of shale oil production on oil pricing is gradually augmenting, it is still relatively minor. Importantly, the DBSTS model can pinpoint crucial shifts in historical data, like the financial crisis of 2008. Conclusively, the DBSTS model with its commendable short-term predictive abilities proves ideal for crude oil price analysis.

This study [42], develops a predictive framework for Ecuador's energy sector using the Long-range Energy Alternatives Planning (LEAP) [63], model. The intent is to probe the transformation of the energy matrix, under variable energy forecasts and efficiency policy scenarios, employing a detailed bottom-up analysis and aligning with Ecuador's recent political and infrastructural developments. According to the developed model, the final energy consumption is expected to reach 158 million Barrels of Oil Equivalent (BOE) by 2030, with transportation being the dominant consuming sector. The study underscores the significant role of hydroelectric power in Ecuador's energy planning. Predicted hydroelectric generation is projected to hit 63,513 GWh in 2030, more than triple the generation levels of 2010. The study also anticipates energy savings of 15 million BOE and an associated decrease in Greenhouse Gas (GHG) emissions, thanks to the PEC energy efficiency program, which encourages the use of induction stoves over LPG stoves in households. Further, the research indicates that implementing energy efficiency policies in the transportation sector could curb the consumption of oil products by nearly 3% in a high-growth scenario, potentially benefiting the industrial sector. However, the study also raises concerns about the imminent drop in oil self-sufficiency, expected to last only 15 years beyond 2030.

This research delves into the interconnectedness of crude oil prices and the market indices of banking sectors within oil-exporting economies in the Gulf Cooperation Council (GCC) [43]. It employs daily data spanning the years 2010 to 2017, considering global banking impacts (via the S&P500 Banking Index) and interest rates (measured by Treasury Bills). The study utilized dynamic ordinary least squared (DOLS) and fully modified ordinary least squared (FM-OLS) methodologies, which revealed that crude oil prices have a positive impact on banking indices until they reach $95 per barrel. Beyond this value, the impact inverts and becomes detrimental, mirroring similar patterns detected in the US equity market. The research further establishes a positive influence of the S&P500 Banking Index on the GCC banking sector, whereas interest rates display a negative correlation. These findings validate the inverse U-shaped correlation between crude oil prices and banking sector indices. Furthermore, causality analysis identifies reciprocal causalities between the pricing of crude oil, GCC banking sectors, and the US banking sector. The study illuminates a critical non-linear correlation that is key for the management of oil-banking portfolios and the development of strategies to hedge against oil price risk.

This study emphasizes the critical need to employ suitable treatment technologies as part of a transition towards a circular water economy in the oil and gas industry [38]. The focus is particularly on the application of these technologies in treating effluents produced by petroleum refineries in Iran. Implementing these technologies can empower local authorities, governments, investors, and developers to mitigate climate change and water scarcity, reuse treated effluents, and reduce soil, water, and air pollution. Ultimately, this contributes to the development of sustainable communities and green industries. The study aims to strike a balance among various concerns within the framework of sustainability and circularity policies. To this end, it assesses various principles, including environmental, economic, technological, social, and circularity aspects. The study introduces a novel DSS called the Picture Fuzzy Set (PFS)-based Combined Compromise Solution (CoCoSo) or PFS-CoCoSo. This proposed DSS aids in selecting the most appropriate technology considering the principles related to sustainability and circularity pillars.

The critical nature of effective marine oil spill management (MOSM) [64] cannot be overstated, given the catastrophic implications of oil spills. MOSM, a complex system, is influenced by multiple factors such as the properties of the spilled oil and the environmental conditions. The system involves key components like oil spill detection, characterization, and monitoring; risk evaluation; optimization of response selection and process; and waste management. These components necessitate timely decision-making. Implementing robust computational techniques can substantially streamline these decision-making processes. These techniques rely on real-time data (for instance, satellite and aerial observations) and historical records of oil spill incidents. Numerous soft-computing, artificial intelligence-based models, and mathematical techniques have been leveraged for carrying out MOSM's components.

This study revisits the literature published since 2010 concerning the use of computational techniques in MOSM [44]. It includes a statistical evaluation regarding the distribution of papers over time, publishers' involvement, research subfields, the countries where the studies originated, and chosen case studies. The review condenses the key findings reported in the literature for two primary MOSM practices: spill detection, characterization, and monitoring; and spill management and response optimization. It identifies potential gaps in the application of computational techniques in MOSM and proposes a holistic, computation-based framework for enhancing MOSM's effectiveness.

This research explores the connections between air pollution, socio-economic conditions, and confirmed diseases, focusing on an industrial area in Southern France, Etang de Berre, known for its steel industries, oil refineries, and transportation hubs [45]. Utilizing a Bayesian model, 178 variables were integrated, revealing links between exposure to certain air pollutants and specific diseases. Notably, low concentrations of hydrofluoric acid and SO2 were associated with lung and bronchus cancers, while exposure to particulate cadmium disrupted insulin metabolism in elderly people, leading to diabetes. When concentrations of benzo[k]fluoranthene increased, hospital admissions for respiratory diseases also surged. Moreover, the study highlighted the impact of socio-economic factors on disease prevalence and discovered potential lung cancer-causing, diffuse polychlorinated biphenyl (PCB) pollution in the area.

The study underscores the value of credit risk analysis within non-financial companies to circumvent potential counterparty defaults, highlighting the role of credit default swaps in this assessment [46]. However, the need for a better understanding of the price dynamics underlying these swaps calls for data-driven decision-making, and this paper achieves this by applying sentiment and topic analysis to financial analyst reports. This research, which scrutinizes 3386 analyst reports for constituents of the Dow Jones Industrial Average Index from 2009 to 2020, reveals that the sentiment and certain topics within these reports correlate with shifts in the credit default swap spread, even after accounting for established credit risk indicators and financial news. Consequently, it's discovered that these reports contain crucial information that can enhance our comprehension of existing risk evaluations. The findings suggest that banks and corporate risk managers can enrich their existing financial metrics and financial news data with insights gleaned from analyst reports.

The study presents an integrated DSS that unifies business and engineering processes through a dashboard interface [47]. This interactive platform enables a two-tiered decision-making model powered by optimization and agent-based mechanisms. Initially, decision-makers establish values for certain variables which, when inputted into the system via the dashboard, instigate a multi-objective robust optimization problem. This issue, informed by a holistic business and engineering simulation model, delivers values for the next sequence of decision variables. This cyclical decision-making process is executed until a state of equilibrium is reached, as exemplified through an oil refinery case study.

Addressing the complex issue of forecasting crude oil prices, this paper proposes a hybrid model that capitalizes on complex network analysis and deep learning techniques, specifically long short-term memory (LSTM) [48]. Given the unpredictable, nonlinear, and highly volatile nature of oil prices, the model uses a visibility graph - a tool in complex network analysis - to cast the dataset onto a network. To extract the nonlinear features of crude oil prices and restructure the dataset, the authors then employ K-core centrality. This analytical approach aids in uncovering nonlinear features and reorganizing the data. Once pre-processed, the LSTM is implemented to model the restructured data. The model's effectiveness is substantiated by comparing empirical outcomes with those from previous studies. The proposed model proves to be not only highly accurate and robust but also a dependable method for predicting crude oil prices.

Researchers in [49], proposed a novel DSS that amalgamates the analytical network process (ANP), decision-making trial and evaluation laboratory (DEMATEL), and multi-objective optimization (MULTIMOORA) methods under the umbrella of fuzzy set theory to prioritize sustainable Advanced Pollution Control Technologies (APCTs) implementation. Evaluating three distinct cases from Iran's petrochemical, gas, and oil refineries, the DSS assessed prevalent APCTs, including Electrostatic precipitators, Fabric filters, Wet scrubbers, and Cyclones. The findings, structured sequentially, highlight the system's feasibility for group decision-making amid expert opinions and data uncertainties, aiding in aligning energy and carbon management (ECM) policies with sustainability and green growth objectives. A subsequent sensitivity analysis further validates the robustness of our approach in prioritizing these technologies.

Researchers in [50], proposed a DSS tailored for informed investments in new VCO agro-industries. This system augments traditional management methods by integrating natural data with economic analysis, encompassing spatial analysis, location quotient, capacity production planning, and financial scrutiny. Utilizing four case studies cantered on Pariaman District, West Sumatera, Indonesia, the viability of VCO investments was examined. While the current DSS streamlines decision-making for investors, it requires enhancements to transition into a fully online, overlay-free application.

In [51], researchers propose a decision support system to enhance the throughput capacity of key oil pipeline sections. Utilizing automation algorithms and optimization techniques, the system identifies cost-effective investment project improvements, factoring in returns and projected profits. The aim is to streamline design alternatives based on past projects and current pipeline technicalities. By examining prior optimization efforts and historical pipeline data, and developing automated solutions for hydraulic and economic issues, the team introduces a methodology for quickly elevating oil pipeline capacity, merging hydraulic analysis with an optimization algorithm.

Researchers in [52], investigated the potential of the "drone emprit" tool to monitor and predict fuel price trends using data sourced from Twitter. They sought to create a novel method to understand and forecast fuel price shifts by tapping into the vast reservoir of data on social media. This research merges visuals from drone emprit at fuel distribution sites with sentiment analysis from social media. Their approach includes capturing visual data, collecting textual data from online platforms, and then undertaking a combined data analysis. The study's outcomes shed light on social and economic drivers behind fuel price hikes, evident in online dialogues. This unique blend of visual and textual data analysis offers a fresh method to understand and anticipate economic trajectories.

In [53], researchers introduced a method to pinpoint and assess key success factors for oil and gas (O&G) projects, focusing on challenging environments like Iran. Drawing from a wide literature review, they refined 197 indicators down to 34. Through exploratory factor analysis (EFA), seven core success factors emerged, later validated via confirmatory factor analysis (CFA). The study also showcased a novel two-step fuzzy inference system for project evaluation, tested on five Iranian O&G projects. This work stands out for its fusion of statistical and mathematical techniques, forging a resilient model for evaluating O&G projects in uncertain settings, utilizing a decision support system (DSS) and an advanced fuzzy inference system (FIS).

Researchers in [54], proposed a strategy to support the Indonesian government's ambitious goal of boosting oil production to meet the nation's growing petroleum demand. Targeting a production level of 1 million BOPD and 12 BSCFD by 2030, one of the key strategies under IOG 4.0 is the creation of a web-based oil and gas showroom platform. Designed as an e-showroom, this platform aims to simplify the process for potential investors to discover and familiarize themselves with promising areas in Indonesia.

Researchers in [55], proposed an innovative approach to oil & gas reservoir navigation using 3D generative modelling combined with a hybrid of physics and AI/ML techniques. The team first simulated a logging survey to analyze electromagnetic tool responses. By employing probabilistic inverse mapping, they sought optimal well placement in various workflow scenarios. The methodologies were then consolidated into deployable software notebooks, enhanced by parallel computing and 3D visualization. These notebooks, equipped with supercomputing-on-chip capabilities and user-friendly interfaces, are tailored for rapid iterations, benefiting both in-house experts and early adopters in the industry.

In [56], researchers explore the essential role of project control systems (PCS) in achieving project success. Utilizing a mixed-method approach, the study evaluates six PCS elements using data from 400 project managers in Saudi Arabia's petroleum and chemical sectors. Findings highlight the critical nature of PCS for meeting cost objectives, with Project Governance identified as the primary PCS factor. The research also reveals that standardized processes are lacking, hindering effective governance, while experienced project teams enhance earned value implementation. This study offers insights into the significance of specific PCS elements and their individual enablers and barriers.

In comparing our proposed work for the thesis to the related works in the field, it becomes evident that our model presents a novel and highly innovative approach to addressing the challenges faced by the oil refinery industry, particularly in the realm of workflow transformation and economic analysis. While the related works offer valuable insights into various aspects of the industry, such as data analysis, environmental impact assessment, and decision support systems, they often tackle these issues in isolation. In contrast, our proposed work stands out by offering a comprehensive and integrated solution that addresses multiple critical challenges concurrently.

First and foremost, our model seeks to revolutionize the way data is managed and decisions are made in the oil refinery sector by transitioning from traditional tools like Excel to a modern web-based DSS. Unlike the related works, which may emphasize specific aspects of data analysis or environmental impact assessment, our approach focuses on the complete transformation of refinery workflows, encompassing data handling, collaboration, and decision-making processes. This comprehensive shift from Excel to a web-based DSS is a fundamental departure from the status quo and holds the promise of significantly enhancing operational efficiency. Furthermore, our proposed work introduces advanced analytics capabilities within the DSS, going beyond the scope of most related works. While some related works touch upon data analysis, our model incorporates cutting-edge features such as advanced statistical analysis, predictive modelling, machine learning algorithms, and data visualization. This empowers decision-makers in the oil refinery industry with tools to perform complex data analysis that was previously challenging or impossible with traditional methods. A crucial aspect that sets our work apart is the integration of economic analysis features into the system. While economic viability is a vital consideration for decision-makers in the industry, few related works delve deep into this aspect. Our model allows users to assess the long-term economic implications of their decisions, including forecasting, cost-benefit analysis, return on investment calculations, and other economic metrics. This economic analysis feature is invaluable for strategic decision-making, as it provides a holistic view of the financial impact of various choices. Lastly, our proposed work aims to facilitate real-time data processing and reporting, providing up-to-date insights that can drive informed decision making a feature not extensively explored in most related works. This real-time aspect ensures that decision-makers have access to the most current information, enabling them to adapt swiftly to changing conditions and make timely, data-driven choices.

In summary, while related works offer valuable contributions to specific facets of the oil refinery industry, our proposed work for the thesis takes a pioneering approach by introducing a holistic and transformative model. By transitioning to a modern web-based Decision Support System, incorporating advanced analytics and economic analysis, and enabling real-time data processing, our model promises to revolutionize how the industry manages workflows, makes decisions, and ultimately achieves greater efficiency and profitability. This represents a significant step forward in the field of oil refinery workflow transformation with economic analysis [83]. Highlighted a novel approach to maintaining the quality of air in operating rooms. The authors presented a neuro-fuzzy inference system (FIS) and an integrated model of the neuro-fuzzy inference system (ANFIS) to control contamination through optimal airflow distribution. The essence of this control is to ensure surgical procedures are performed with utmost accuracy. The work showcased a deep learning technique aimed at predicting incidences related to airborne contamination. The primary objective was to create a surgical environment with minimal airborne contaminants and to decrease the likely incidence during surgeries. The neuro-fuzzy deep learning model utilized a neural network framework, focusing on three key parameters affecting air quality. The practical application of this methodology involved data gathered by sensors in a real-world operating room in Mashhad, Iran. The results from this study indicated a validation accuracy of 97.3% for relative humidity and 95% for particle estimation, showcasing the effectiveness of the neuro-fuzzy model in improving indoor air quality [84]. Explored the realm of Big Data and Decision Support Systems (DSS) in ensuring food safety. As technology continues to evolve, handling vast amounts of diverse data has become imperative. Within the food supply chain, information is dispersed, exhibiting variance in format, size, and origin. The study delved into the intricate relationship between environmental elements, food contamination, and foodborne ailments. The review provided a detailed look at the architecture of Big Data and web technologies concerning food safety, particularly in light of climate change impacts. The article also presented challenges in integrating Big Data into food safety and provided a roadmap for future research avenues in the food supply domain [85]. Discussed the transformative impact of artificial intelligence (AI) on healthcare delivery and research. The paper underscored the importance of fostering collaborations between AI developers and healthcare professionals to harness the full potential of AI. This synergy between AI and medical professionals promises advancements in various domains, including personalized medicine, clinical decision support systems, healthcare process optimization, and patient engagement. The work showcased how AI, when integrated with patient data, can result in enhanced diagnostic accuracy, timely disease detection, and precision in treatment plans. The collaboration also aims to develop personalized medicine techniques, optimizing treatments based on genetic markers, biomarkers, and clinical indications. In addition, the study emphasized the significance of ethical considerations and regulatory compliance. The future of healthcare, as suggested by the authors, lies in the seamless integration of AI technologies with medical expertise, fostering innovation and optimizing patient outcomes.

[86]. Traces the historical development of Decision Support Systems (DSS) and their impact on various sectors, especially in power management and smart grid planning. The genesis of DSS can be linked back to the abstract studies in decision making at the Carnegie Institute of Technology and the computer system interaction research at the Massachusetts Institute of Technology in the 1960s. The 1970s saw an expansion in DSS within academia, including notable journal and conference publications. The 1980s marked the introduction of DSS in China, with the 1990s witnessing a diversification of applications, particularly through data warehousing and online logical processes. The evolution of cloud computing has further advanced DSS, allowing for cloud-based decision-making tools. Over the last three decades, more than 20 different techniques for implementing DSS have emerged, each primarily project-oriented and difficult to compare in terms of efficacy. The involvement of DSS in sectors like electricity and transportation has been notable, with advanced technologies and novel architectures being integrated into electrical power systems. This integration aims to enhance energy efficiency and optimize resource allocation, contributing to the development of smart grids. The gradual transition towards smart grids involves both the adaptation of existing systems and the creation of new ones, taking into account the interests of all stakeholders. Decision-making within this context is critical for analyzing each component of the smart grid, its costs, and the feasibility of deployment [87]. Presents a novel fuzzy decision-making model to evaluate the sustainability index (SI) of industries listed on the stock exchange. The study employs a two-step approach: firstly, it determines the weights of 12 different SI criteria using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) methodology based on Quantum Spherical Fuzzy Sets (QFS) with a golden cut. Secondly, it ranks the SI performances of 10 industry alternatives through the extended Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with QFS. This study introduces an original fuzzy decision-making methodology to identify significant sustainability criteria for companies. The analysis reveals that renewable energy usage is a key criterion affecting other SI aspects. This observation suggests that industries, particularly in communication and IT, can enhance their SI by focusing on renewable energy, which in

turn can address carbon emission challenges and improve business reputation. The study also suggests the integration of microgrid energy management systems as a solution to the high costs associated with renewable energy projects, allowing for cost-sharing and increased adoption of sustainable energy sources [88]. Focuses on the decision-making process for energy-efficient retrofitting of residential buildings. With changing building regulations driving the trend towards high-performance residential buildings, the study aims to develop a performance-oriented decision support workflow for retrofitting. The proposed method, applied in a hypothetical multifamily apartment block context in Istanbul Province, involves an automated parametric energy simulation combining Energy Plus and MATLAB®. This simulation assesses the differences in retrofit alternatives based on building envelope, energy systems, and renewable energy systems. Additionally, the study uses a multiple-criteria decision analysis to select retrofit alternatives that balance primary energy savings with life-cycle cost savings. This approach is designed to aid architects and homeowners, the primary decision-makers in this context, in making informed choices about performance-based retrofitting. The workflow enables a comparative analysis of energy and economic performance across various retrofitting alternatives, facilitating more efficient decision-making in the complex process of residential retrofitting.

[89]. Explores the integration of Decision Support Systems (DSS) in the energy sector, particularly focusing on geothermal energy exploration. It emphasizes the complexities inherent in geothermal resource exploration, involving numerous conflicting criteria and extensive data analysis. This study highlights the role of Geographic Information Systems (GIS) in enhancing data analysis and dissemination within this context. The research proposes an innovative approach to minimize the disconnect between GIS and geothermal exploration by employing a Spatial Decision Support System (SDSS). This system integrates data from various sources into a Multi-Criteria Decision Analysis (MCDA) model, aiding in identifying potential areas for detailed exploration. The study also introduces combinatorial optimization algorithms to tackle the problem of prioritizing geothermal well drilling sites, notably employing the Metropolis-Hasting and Genetic algorithms. The implemented Web-based SDSS model demonstrated significant efficacy in locating optimal geothermal wells, as evidenced by the case study of Kenya's Olkaria geothermal field.

[90]. Investigates the deployment of predictive maintenance within the industry 4.0 paradigm, emphasizing its vital role in industrial operations. This research presents a

prototype DSS that leverages machine learning and AI algorithms to detect deviations in industrial processes, enabling timely interventions. The DSS, developed using open-source R packages, aligns with the needs of small and medium enterprises (SMEs) by offering a cost-effective and flexible solution for real-time industrial equipment maintenance. The system's effectiveness is validated through a case study focusing on predictive maintenance of industrial cooling systems, where simulated data informed by in-depth interviews are utilized. The study highlights the advantages of using open-source tools like R for SMEs, including cost savings and customization options, while also acknowledging the challenges and concerns related to its implementation in industrial infrastructures.

[91]. Discusses the evolving dynamics of power systems, particularly in response to the energy transition characterized by electrification, digitalization, and decarbonization. This paper delves into the impact of these changes on control centers, necessitating a shift in operational paradigms. It advocates for transformative changes beyond incremental hardware and software upgrades, emphasizing the need for human-centered design approaches in power system management. The study presents a vision for evolving control room operations, suggesting a unified hyper vision scheme grounded in structured decision-making concepts. This approach aims to equip operators with enhanced capabilities for proactive, collaborative, and efficient management of complex and dynamic power systems. The proposed architecture integrates emerging technologies and real-time automation, emphasizing continuous operation planning and monitoring across various time horizons.

These studies collectively underline the significance of advanced decision support and predictive maintenance systems in optimizing resource allocation, ensuring efficient energy use, and enhancing operational efficiencies across various sectors, from energy exploration to industrial maintenance and power system management.

3. SYSTEM DESIGN AND DEVELOPMENT PROCESS

3.1 PROJECT OBJECTIVE

The use of Excel as a tool for managing and processing large amounts of data, while it has proven effective over the years, presents several limitations, particularly when used in complex domains such as refinery economics.

One of the key limitations of Excel is its difficulty in handling large datasets. As data scales up, Excel can become slow, unresponsive, and even crash, resulting in a loss of data and work. Furthermore, Excel is not designed to handle multi-user collaboration, which means only one user can edit a document at a time. This leads to inefficiencies in a team-based environment where multiple individuals need to input or modify data simultaneously. Excel also lacks strong data validation features. While it does provide basic data validation, it can be time-consuming and complex to set up for large datasets. As a result, data errors can easily occur and go unnoticed, potentially impacting the accuracy of the refinery economic model.

In terms of data security and control, Excel falls short. Spreadsheets can be easily copied, edited, or deleted, leading to data integrity issues. They also do not provide an audit trail of changes, making it difficult to track modifications or identify when an error was introduced. Transforming this Excel model to a web-based application addresses these challenges. A well-designed web application can handle large datasets efficiently, provide robust data validation features, and support simultaneous multi-user access, thereby enhancing collaboration.

In terms of security, a web application provides stronger control over data. It can track user activities, providing a comprehensive audit trail and ensuring data integrity. It can also implement advanced security measures to protect sensitive data, such as encryption and user authentication. In addition, a web application offers the possibility of integrating with other systems or data sources, providing a more holistic view of the refinery's operations. It also allows for real-time data processing and reporting, providing up-to-date insights for decision making. Thus, the transition from the Excel model to a web-based application is not only necessary but crucial for managing complex refinery economic data more effectively and securely.

3.2 SYSTEM REQUIREMENTS

3.2.1 Functional Requirements

Functional requirements detail what the system should do. For the Refinery DSS, these include:

a. Create Input Sheets: The system must provide users with the capability to create new input sheets, capturing the necessary parameters and data required for subsequent computations and analyses [65].

b. View Input Sheets: The system must allow users to access and review existing input sheets, providing visibility into all parameters and data used in the refinery economic models [66].

c. Edit Input Sheets: The system must facilitate modifications to existing input sheets, ensuring the parameters and data within these sheets remain current and accurate over time [67].

d. Delete Input Sheets: The system must permit the deletion of input sheets that are no longer needed, thereby supporting efficient data management [68].

e. Generate Calculation Sheets: The system must be able to generate detailed calculation sheets based on data from selected input sheets, offering valuable insights into the refinery economics [69].

3.2.2 Non-Functional Requirements

Non-functional requirements define the system's operational characteristics. For our web-based DSS, the following non-functional requirements have been identified [70]:

a. Performance: The system must provide timely responses to user interactions. For example, the time taken to load input sheets or calculation sheets should not exceed a pre-defined threshold, such as 2 seconds, thus ensuring a smooth and efficient user experience [71].

b. Scalability: The system must be able to manage increasing amounts of data as the company's operations expand, ensuring its performance remains consistent irrespective of the data volume [72].

c. Security: The system must incorporate robust security measures to protect sensitive refinery data, including secure data storage and strict access controls to prevent unauthorized access [73].
d. Usability: The system must be user-friendly, featuring an intuitive interface and providing clear instructions to users, thus enhancing their ability to navigate the system and perform necessary tasks efficiently [74].
e. Reliability: The system must offer high availability to ensure users have continuous access to the critical data and insights it provides [75].

3.3 SYSTEM DESIGN

The transformation from an Excel-based system to a web application involves restructuring the functionality of Excel components into an interconnected, user-friendly online interface. This section delves into the design of the newly created web-based model, showcasing how it accommodates the components of the initial Excel system: the dashboard, input sheet, output sheet, and calculation sheet.

3.3.1 User Interface Design

3.3.1.1 Sitemap

All In the sitemap provided, the interfaces are organized as main categories under the Home page. Each main category (e.g., User Dashboard, Input Sheets, Dashboard Interface, Calculation Sheets) represents a key section of the DSS application. Each of these sections will have its own pages or views. For example, under the "Input Sheets" section, there are several different pages/views: "Sheet List," "New Sheet," "Edit Sheet," and so on. These are all separate interfaces, but they are part of the "Input Sheets" section of the application.

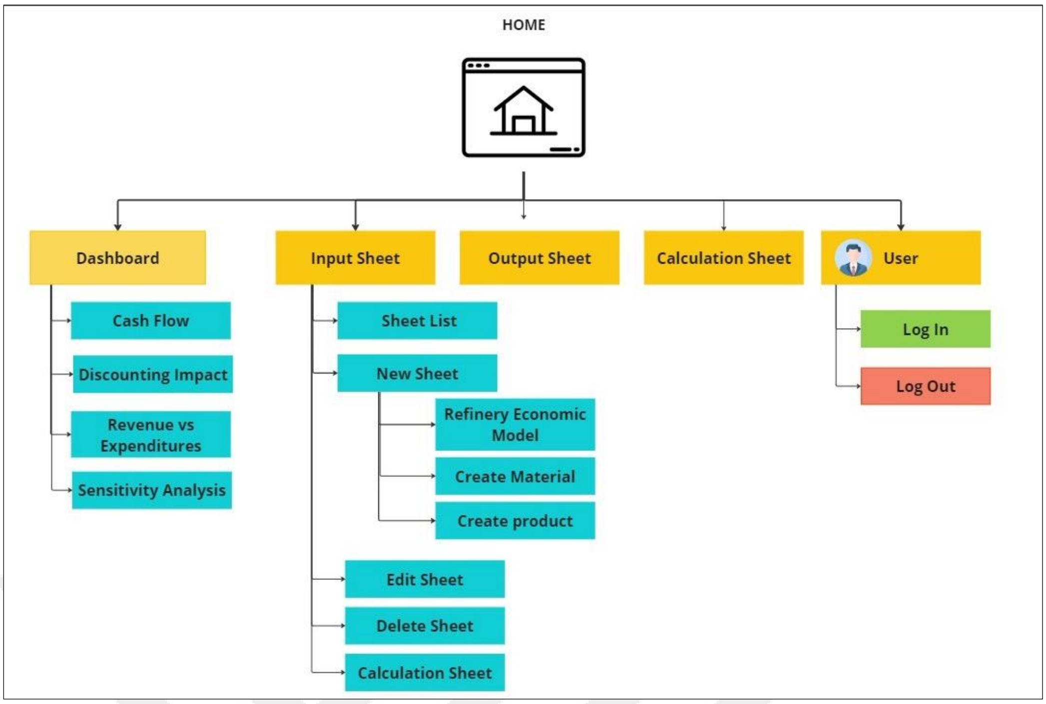


Figure 3.1: The Web-Based DSS Sitemap.

3.3.1.2 Interface layout

The application utilizes a consistent dashboard layout across all its interfaces for ease of navigation and a unified user experience. The interface is divided into three main sections:

Header: The header is consistently present across all pages. It includes on the far right of the header, user-specific options like account settings, research and logout are accessible.

Navigation Sidebar: Positioned on the left side of the screen, the navigation sidebar provides access to different sheets in the application. This includes buttons for the Input Sheet, Output Sheet, Calculation Sheet, and others. Users can switch between different sheets by clicking on these buttons.

Main Content Area: The large, central area of the interface displays the content of the selected sheet. Depending on the user's selection in the navigation sidebar, this area can show various forms for data input, tables for displaying output, complex calculations, and more.

With this structure, users can easily navigate between different parts of the application and always have a clear understanding of their current context. The consistent layout also reduces the learning curve for users, allowing them to become comfortable with the application's operations more quickly.

Figure 3.2: The DSS Interface Layout.

3.3.2 User Flows

3.3.2.1 User case diagram

The application presents a variety of use cases designed to facilitate user interaction and make the workflow as smooth as possible.

a. Logging In is the initial gateway into the application. Users provide their registered username and password, which the system verifies. Successful authentication grants access to the user, directing them to the home page. Conversely, if authentication fails, an error message informs users, prompting them to attempt again.

b. The user then has the ability to Create Input Sheets directly from the home page. Upon choosing this option, the system provides a blank template where users can input necessary information. Once completed and submitted, the system saves the input sheet and validates its successful creation to the user.

c. A vital aspect of the application is the Dashboard. Accessible from the home page, this area provides an overview of key statistics and visuals such as cash flow (CF), revenue versus expenditures, and sensitivity analyses.

d. Another essential use case involves Generating Calculation Sheets. Users can select an input sheet and instruct the system to generate a corresponding calculation sheet. The system processes the request, performs the required calculations based on the chosen input sheet, and presents a comprehensive calculation sheet to the user. Users also have the ability to View Input Sheets. Upon selection from the home page, the system retrieves and displays a list of all available input sheets. Users can select any input sheet from the list, prompting the system to show its details.

e. Input sheets are not static; users can Edit Input Sheets. While viewing an input sheet's details, users can opt to edit the content. The system presents the editable fields, allows the user to make changes, and saves these modifications once submitted, confirming the successful update.

f. Finally, the system offers the capability to Delete Input Sheets. From an input sheet's details, users can select the delete option. The system seeks user confirmation before proceeding. Once confirmed, the input sheet is removed from the system, and the successful deletion is communicated to the user.

g. Navigate Sheet List is another essential feature that improves the user experience of the application. Once users are on the home page, they have the ability to navigate through the list of available sheets. This list includes all the input sheets and calculation sheets that have been created. This use case is critical as it allows users to locate the specific sheet they are interested in quickly and easily. Whether they wish to view, edit, delete, or generate a calculation sheet from an input sheet, navigating the sheet list is the first step in these processes.

Figure 3.3: Use Case: Creating New Input Sheet.

3.3.2.2 Class diagram

The class diagram showcases the main classes and their relationships in the DSS application. The User class represents the users of the application, the InputSheet class represents the input data provided by the users, the CalculationSheet class represents the calculated data from the economic model, and the Dashboard class represents the visualizations and graphs for data analysis. The SheetList class acts as a container for managing multiple input sheets.

a. User Class:

a) Represents a user of the DSS application.

b) Contains properties such as UserID, Username, Password, and Email.

c) Provides methods for user authentication and profile management.

b. Inputsheet Class:

a) Represents an input sheet in the DSS application.

b) Contains properties that store input data for the economic model, such as Capacity, CAPEX, DebtPercent, EquityPercent, RefineryLife, and more.

c) Provides methods for creating, editing, and deleting input sheets.

ProductRevenue, RawMaterialCost, and RefineryEconomicModel are sub classes from the inputSheet class and are used to compute and store the financial aspects of the refinery's operations. The ProductRevenue class calculates the revenue generated from different products, while the RawMaterialCost class calculates the cost of raw materials. The RefineryEconomicModel class stores the economic model of the refinery, including parameters such as capacity, CAPEX, debt, and equity. These classes play a crucial role in the decision-making process of the refinery industry by providing insights into profitability, costs, and financial performance.

c. Productrevenue Class:

a) Represents the revenue generated from the production of different products in the refinery.
b) Contains properties such as Product, PricePerTon, CapacityTonPerDay, IncomeKPerDay and IncomeMilPerYear.
c) Provides methods for computing the income based on the price and capacity.

d. Rawmaterialcost Class:

a) Represents the cost of raw materials used in the refinery process.
b) Contains properties such as Material, PricePerTon, CapacityTonPerDay, CostKPerDay, and CostMilPerYear.
c) Provides methods for computing the cost based on the price and capacity.

e. RefineryEconomicModel Class:

a) Represents the economic model of the refinery.
b) Contains properties such as RefineryName, Capacity, CAPEX, DebtPercentage, EquityPercentage, RefineryLife, DiscountRate, YearlyOperation, GovTax, Inflation, CrudeOilPrice, DebtDuration and InterestRate.
c) Provides methods for performing financial calculations, such as computing EQUITY%, and manipulating the economic model data.

f. CalculationSheet Class:

a) Represents the calculation sheet that contains various financial metrics and calculations for the refinery.
b) Contains properties such as CalculationSheetID, InputSheetID, Revenue, OPEX, EBITDA, Depreciation, EBIT, Loan, PrincipalPayment, InterestPayment, DebtPayment,

Tax, Profit, CashFlow, AccumulativeCashFlow, DiscountedCashFlow, and DiscountedAccumulativeCashFlow.

c) Contains sub-classes for specific financial calculations and metrics.

a. IRR (subclass of CalculationSheet):

a) Represents the internal rate of return (IRR) calculation for the refinery.

b) Contains properties such as IRRValue.

b. CashFlow (subclass of CalculationSheet):

a) Represents the cash flow analysis for the refinery.

b) Contains properties such as CashFlowValues and AccumulativeCashFlowValues.

c. CAPEX (subclass of CalculationSheet):

a) Represents the capital expenditure (CAPEX) analysis for the refinery.

b) Contains properties such as CAPEXValues and NPVValues.

d. OPEX (subclass of CalculationSheet):

a) Represents the operating expenditure (OPEX) analysis for the refinery.

b) Contains properties such as OPEXValues and NPVValues.

These subclasses of CalculationSheet are focused on specific financial aspects of the refinery's operations. The IRR class calculates the internal rate of return, providing insights into the profitability of the project. The CashFlow class analyzes the cash flow, tracking the inflows and outflows of funds over time. The CAPEX class analyzes the capital expenditure, including the costs and net present value (NPV) associated with investments. The OPEX class analyzes the operating expenditure, including costs, NPV, and other financial metrics related to operational expenses. These subclasses help in evaluating the financial performance and viability of the refinery project.

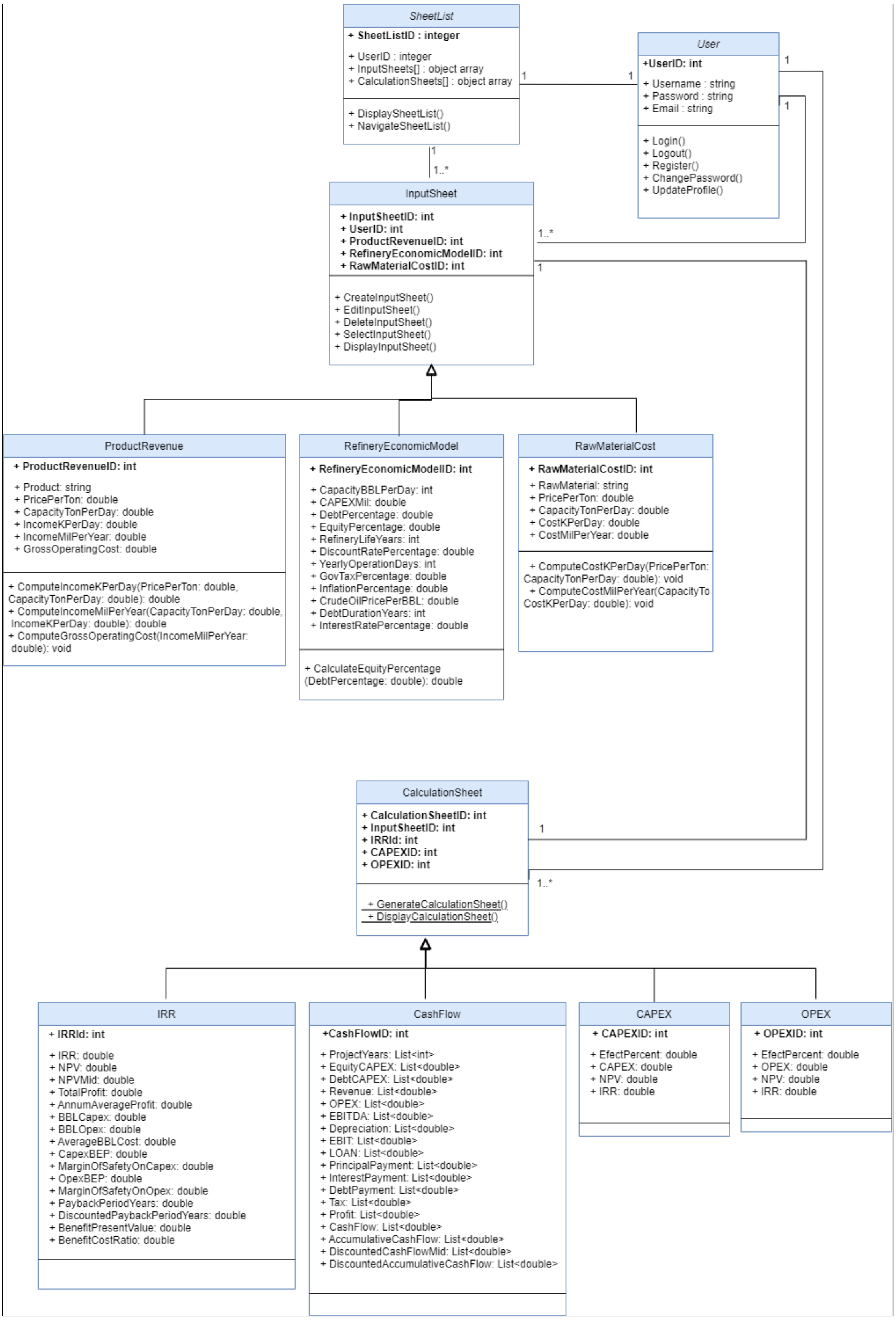


Figure 3.4: The DSS Class Diagram.

3.4 CALCULATION FORMULAS

In this section, we will outline the formulas used for the calculations in the financial analysis tool. These formulas are applied to various variables and data points to derive meaningful insights and metrics. Below are the key formulas used:

3.4.1 Input Sheet Calculations

a. Create Material: The equation calculates the Material Cost per day (K$/d) by multiplying the Price per ton ($) with the Capacity per day (ton/d) and dividing the result by 1000. This equation determines the cost of materials required for production on a daily basis as eq (3.1).

$$\text{Cost (K\$/d)} = \text{Price (\$/ton)} * \text{Capacity (ton/d)} / 1000 \tag{3.1}$$

The equation calculates the Material Cost per year (Mil $/y) by multiplying the Material Cost per day (K$/d) with the Yearly Operation (Day) and dividing the result by 1000. This equation estimates the cost of materials required for production over the course of a year as eq (3.2).

$$\text{Cost (Mil \$/y)} = \text{Cost (K\$/d)} * \text{Yearly Operation (Day)} / 1000 \tag{3.2}$$

The equation calculates the Gross Operating Cost by summing up the Material Cost per year (Mil $/y) for all materials used in the production process. It provides the total cost of operating the refinery, taking into account the costs associated with each material basis as eq (3.3).

$$\text{Gross Operating Cost} = \sum \text{Cost (Mil \$/y) for all materials} \tag{3.3}$$

b. Create product: The equation calculates the Income per day (K$/d) for a specific product by multiplying the Price per ton ($) with the Capacity per day (ton/d) and dividing the result by 1000. This equation estimates the revenue generated from the production of a particular product on a daily basis as eq (3.4).

$$\text{Income (K\$/d)} = \text{Price (\$/ton)} * \text{Capacity (ton/d)} / 1000 \tag{3.4}$$

The equation calculates the Income per year (Mil $/y) for a specific product by multiplying the Income per day (K$/d) with the Yearly Operation (Day) and dividing the result by 1000.

This equation estimates the revenue generated from the production of a particular product over the course of a year as eq (3.5).

$$\text{Income (Mil \$/y)} = \text{Income (K\$/d)} * \text{Yearly Operation (Day)} / 1000 \qquad (3.5)$$

The equation calculates the Gross Production Revenue by summing up the Income per year (Mil $/y) for all products. It provides the total revenue generated from the production of all products as eq (3.6).

$$\text{Gross Production Revenue} = \sum \text{Income (Mil \$/y)} \qquad (3.6)$$

3.4.2 Calculation Sheet

The calculation sheet contains four tables; we will describe the features and formulas to compute each one.

Table 1: Equity Capex represents the equity capital expenditure for the given year. It is computed by multiplying the total CAPEX (Capital Expenditure) in million dollars by the equity percentage and dividing it by 4 as eq (3.7).

$$\text{EQUITY CAPEX} = (\text{CAPEX} * \text{EQUITY\%}) / 4 \qquad (3.7)$$

DEBT CAPEX: IT calculates the debt capital expenditure for the given year. The formula multiplies the total CAPEX in million dollars by the debt percentage and divides it by 4 as eq (3.8).

$$\text{DEBT CAPEX} = \text{CAPEX (Mil. \$)} * \text{DEBT} / 43 \qquad (3.8)$$

REVENUE (n): This formula calculates the revenue for the given year (n). It takes the gross production revenue and multiplies it by (1 + inflation) raised to the power of (n - 5). This represents the increase in revenue due to inflation over the baseline year as eq (3.9).

$$\text{REVNIUE (n)} = \text{Gross Production Revenue} * (1 + \text{Inflation}) \wedge (n - 5) \qquad (3.9)$$

OPEX (n) represents the operating expenses for the given year (n). It is computed by multiplying the gross operating cost by (1 + inflation) raised to the power of (n - 5). The negative sign indicates that it is a cost and not a revenue as eq (3.10).

$$\text{OPEX (n)} = -\text{Gross Operating Cost} * (1 + \text{Inflation})\wedge(n - 5) \qquad (3.10)$$

EBITDA represents Earnings Before Interest, Taxes, Depreciation, and Amortization. It is calculated by adding the revenue to the negative value of the operating expenses. The negative sign is applied to the OPEX value to indicate that it is subtracted from the revenue as eq (3.11).

$$\text{EBITDA} = \text{Revenue} + (-\text{OPEX}) \tag{3.11}$$

DEPRECIATION calculates the depreciation expense for the given year. It is computed by dividing the total CAPEX (Capital Expenditure) in million dollars by 24, representing the depreciation over a 24-year period as eq (3.12).

$$\text{DEPRECIATION} = \text{CAPEX (Mil.\$)} / 24 \tag{3.12}$$

EBIT calculates the Earnings Before Interest and Taxes. It is computed by subtracting the depreciation expense from the EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization) as eq (3.13).

$$\text{EBIT} = \text{EBITDA} - \text{DEPRECIATION} \tag{3.13}$$

LOAN (n) calculates the loan amount for the given year (n). It is computed by taking the loan amount from the previous year (n-1) and adding the debt capital expenditure for the current year (n) as eq (3.14).

$$\text{LOAN (n)} = \text{LOAN (n-1)} + \text{DEBT CAPEX (n)} \tag{3.14}$$

PRINCIPAL PAYMENT calculates the principal payment for the given year. It is computed by multiplying the total CAPEX (Capital Expenditure) in million dollars by the debt percentage and dividing it by the debt duration as eq (3.15).

$$\text{PRINCIPAL PAYMENT} = \text{CAPEX (Mil.\$)} * \text{DEBT \%} / \text{DEPT DURATION} \tag{3.15}$$

INTEREST PAYMENT calculates the interest payment for the given year. It is computed by multiplying the loan amount by the interest rate as eq (3.16).

$$\text{INTEREST PAYMENT} = \text{LOAN} * \text{INTREST RATE} \tag{3.16}$$

DEBT PAYMENT calculates the total debt payment for the given year. It is computed by subtracting the principal payment and the interest payment from zero. The sum of the principal payment and the interest payment is negated by multiplying it by -1, resulting in the total debt payment for the given year as eq (3.17).

$$\text{DEBT PAYMENT} = -\left(\text{PRINCIPAL PAYMENT} + \text{INTEREST PAYMENT}\right) \quad (3.17)$$

TAX calculates the tax amount for the given year. It is computed by multiplying the EBIT (Earnings Before Interest and Taxes) by the government tax rate and negating the result as eq (3.18).

$$\text{TAX} = -\text{EBIT} * \text{GOV.TAX} \quad (3.18)$$

PROFIT calculates the profit for the given year. It is computed by adding the EBIT (Earnings Before Interest and Taxes), debt payment, and tax bsis as eq (3.19).

$$\text{PROFIT} = \text{EBIT} + \text{DEBT PAYMENT} + \text{TAX} \quad (3.19)$$

CASH FLOW calculates the cash flow for the given year. It is computed by adding the EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization), debt payment, tax, and equity capital expenditure as eq (3.20).

$$\text{CASH FLOW} = \text{EBITDA} + \text{DEBT PAYMENT} + \text{TAX} + \text{EQUITY CAPEX} \quad (3.20)$$

ACCUMULATIVE CASH FLOW represents the cumulative cash flow for the given year (n). It is computed by adding the cash flow (CF) of the previous year (n-1) to the cash flow of the current year (n) as eq (3.21).

$$\text{ACCUMULATIVE CASH FLOW (n)} = \text{ACCUMULATIVE CASH FLOW}\,(n-1) + \text{CF}(n) \quad (3.21)$$

DISCOUNTED CASH FLOW MID (n) represents the discounted cash flow for the given year (n). It is computed by dividing the cash flow (CF) by (1 + discount rate (DR)) raised to the power of (n - 0.5).

$$\text{DISCOUNTED CASH FLOW MID (n)} = \text{CF} / (1 + \text{DR})\text{\^{}}\,(n - 0.5) \quad (3.22)$$

DISCOUNTED ACCUMULATIVE CASH FLOW (n): This formula calculates the discounted accumulative cash flow for the given year (n). It adds the discounted cash flow of the previous year (n-1) to the discounted cash flow of the current year (n). Let:

a. DCF(n-1) be the discounted cash flow of the previous year (n-1)
b. DCF(n) be the discounted cash flow of the current year (n)

c. DACF(n) be the discounted accumulative cash flow of the current year (n)

Then, the formula for calculating the discounted accumulative cash flow (DACF) for the given year (n) can be expressed as eq (3.23):

$$\text{DACF(n)} = \mathrm{DCF}(n-1) + \mathrm{DCF}(n) \tag{3.23}$$

Table 2:

$$\text{IRR} = \text{TRI} \ (\Sigma \ \text{CASH FLOW (n)}) \tag{3.24}$$

$$\text{NPV (Mil. \$)} = \sum (\text{CACH FLOW}/\ (1 + r)\text{\textasciicircum}t), \text{for } t = 1 \text{ to } n \tag{3.25}$$

In this formula, the cash flows are discounted to their present value by dividing them by (1 + r)^t, where t represents the time period of each cash flow. The discounted cash flows are summed together to calculate the net present value as eq (3.25).

NPV Mid (Mil. $) calculates the net present value for the project. It is computed by summing up the discounted cash flow mid values for all years as eq (3.26).

$$\text{NPV Mid (Mil. \$)} = \Sigma \ \mathbf{DCF\ MID} \tag{3.26}$$

and DCF MID represents the discounted cash flow mid values for each year. The formula sums up all the discounted cash flow mid values to determine the net present value for the project.

Total Profit (Mil. $) calculates the total profit for the project. It is computed by summing up the profit values for all years as eq (3.27).

$$\text{TOTAL PROFIT (Mil. \$)} = \mathbf{\Sigma PROFIT} \tag{3.27}$$

In this representation, Σ denotes the summation symbol, and PROFIT represents the profit values for each year. The formula sums up all the profit values to determine the total profit for the project.

Annum Average Profit calculates the average annual profit for the project. It is computed by dividing the total profit by the sum of equity capital expenditures for all years as eq (3.28).

$$\text{Annum Average Profit} = \text{TOTAL PROFIT (Mil. \$)} \ / \ \Sigma\text{EQUITY CAPEX} \tag{3.28}$$

BBL CAPEX calculates the capital expenditure per barrel of production capacity. It is computed by dividing the total capital expenditure in million dollars by the product of the production capacity in barrels per day, the number of operational days in a year, and the sum of equity capital expenditures for all years as eq (3.29).

BBL CAPEX = CAPEX (Mil.$) * 1000000 / (CAPACITY (bbl/d) * YEARLY OPERATION (DaY) * ΣEQUITY CAPEX) (3.29)

In this representation, Σ denotes the summation symbol, and EQUITY CAPEX represents the equity capital expenditure values for each year. The formula divides the total capital expenditure by the product of production capacity, operational days, and the sum of equity capital expenditures to obtain the capital expenditure per barrel of production capacity.
BBL OPEX calculates the operating expenses per barrel of production capacity. It is computed by dividing the total operating expenses in million dollars (represented as -OPEX) by the product of the production capacity in barrels per day, the number of operational days in a year, and the sum of equity capital expenditures for all years as eq (3.30).

$$\text{BBL OPEX} = -\mathbf{OPEX} * \mathbf{1000000} / (\mathbf{CAPACITY}\ (\mathbf{bbl/d}) * \mathbf{YEARLY\ OPERATION}\ (\mathbf{DaY}) * \mathbf{\Sigma EQUITY\ CAPEX}) \quad (3.30)$$

Average BBL Cost represents the average cost per barrel of production. It is calculated by adding the BBL OPEX (operating expenses per barrel) and the BBL CAPEX (capital expenditure per barrel) as eq (3.31).

$$\text{Average BBL Cost} = \text{BBL OPEX} + \text{BBL CAPEX} \quad (3.29)$$

Margin of Safety on CAPEX represents the percentage difference between the actual capital expenditure (CAPEX) and the depreciation-adjusted CAPEX. It measures the cushion or buffer in the CAPEX budget as eq (3.32).

Margin of Safety on CAPEX = (CAPEX DEP - CAPEX (Mil. $)) / CAPEX DEP (3.30)

In this representation, CAPEX DEP is the depreciation-adjusted CAPEX, and CAPEX (Mil. $) is the actual capital expenditure. The formula calculates the difference between the two values and expresses it as a percentage of the depreciation-adjusted CAPEX. This provides insights into the extent to which the actual CAPEX deviates from the planned or expected CAPEX, allowing for a margin of safety assessment.

Margin of Safety on OPEX represents the percentage difference between the breakeven operating expenses (OPEX BEP) and the actual gross operating cost. It measures the cushion or buffer in the OPEX budget as eq (3.33).

$$\text{Margin of Safety on OPEX} = (\text{OPEX BEP} - \text{GROSS OPERATING COST}) / \text{OPEX BEP} \quad (3.31)$$

In this representation, OPEX BEP is the breakeven operating expenses, and GROSS OPERATING COST is the actual gross operating cost. The formula calculates the difference between the two values and expresses it as a percentage of the OPEX BEP. This provides insights into the extent to which the actual OPEX deviates from the breakeven point, allowing for a margin of safety assessment.

Payback Period (YEARS) represents the number of years required to recoup the initial investment. It is calculated by finding the year in which the accumulated cash flow becomes positive for the first time.

The equation for calculating the payback period (in years) based on the criteria of negative cumulative cash flow is as eq (3.34):

$$\text{Payback Period (YEARS)} = n - (a / b) \quad (3.32)$$

Where:

a. n is the last year in which the cumulative cash flow is negative.
b. a is the absolute value of the cumulative cash flow at the end of the last negative year.
c. b is the cash flow during the year following the last negative year.

The Discounted Payback Period (in years) is a financial metric that measures the time required to recover the initial investment, taking into account the time value of money through discounted cash flows. It is determined by finding the point in time when the cumulative discounted cash flow becomes positive or zero. The mathematical representation of the Discounted Payback Period equation is as follows as eq (3.35):

$$\text{Discounted Payback Period (YEARS)} = n - (a / b) \quad (3.33)$$

In this equation:

a. n represents the year in which the cumulative discounted cash flow becomes positive or zero, indicating the point of recovery.
b. a represents the absolute value of the cumulative discounted cash flow at the end of the last negative year, indicating the remaining investment to be recovered.

c. b represents the discounted cash flow during the year following the last negative year, indicating the cash flow contribution towards the recovery of the investment.

By calculating the Discounted Payback Period, businesses can assess the time it takes to recoup their investment, considering the timing and value of future cash flows.

Benefit Present Value calculates the present value of each cash flow by discounting it back to the present using the discount rate. The discounted cash flows for each year are then summed up to obtain the Benefit Present Value as eq (3.36).

$$\text{Benefit Present Value} = \Sigma(\text{CASH FLOW} / (1 + \text{DISCOUNT RATE})^n) \tag{3.34}$$

The Benefit-Cost Ratio (BCR) is calculated by dividing the Benefit Present Value by the Capital Expenditure (CAPEX) in million dollars. The mathematical equation for the BCR is as follows as eq (3.37):

$$\text{Benefit-Cost Ratio (BCR)} = \text{Benefit Present Value} / \text{CAPEX (Mil. \$)} \tag{3.35}$$

Table 3: To calculate the CAPEX values based on the given effective percentages, you can use the following formulas as eq (3.38):

$$\text{CAPEX} = \text{Base Value} * (1 + \text{Effect Percent}/100) \tag{3.36}$$

In these formulas, the Base Value represents the base CAPEX value of 6000, and the Effect Percent represents the percentage change from the base value. By multiplying the base value by the adjustment factors, you can calculate the resulting CAPEX values for the given effective percentages as eq (3.39).

Table 4:

$$\text{OPEX} = \text{Base Value} * (1 + \text{Effect Percent}/100) \tag{3.37}$$

4. INTERFACES DESIGN

The system is designed to automatically perform the calculations as soon as the necessary input data is provided, offering users an effortless way to understand their cost dynamics. The results are presented in a well-organized, easy-to-read format, making it simple for users to derive meaningful conclusions from the data.

The DSS web application makes the process of creating the input sheet systematic, efficient, and user-friendly. By dividing the process into clear steps, the application guides the user through the data input, ensuring that all necessary information is captured and ready for processing.

4.1 SYSTEM DEVELOPMENT AND CODING

4.1.1 Model-View-Controller (MVC) Pattern

The Model-View-Controller (MVC) [76] design pattern is a widely used software architecture pattern that promotes the division of responsibilities in an application or system to enhance maintainability and scalability. It separates the system into three interconnected components:

a. Model: This represents the data-related logic that the user works with. For example, in a banking software, the Model would define and manipulate data relating to customers, accounts, transactions, etc. In the context of our financial analysis tool, this includes the User, InputSheet, and CalculationSheet classes.
b. View: This is what the user sees and interacts with – the user interface. The View presents the Model's data to the user and also updates when the Model changes. In our application, the View is built with React, a powerful JavaScript library for creating user interfaces.
c. Controller: The Controller is essentially the bridge between the Model and the View. It processes all the user's interactions (inputs) from the View, modifies the data in the Model based on these inputs, and also updates the View to reflect changes in the Model. In our application, the Controllers are created using Express.js, a flexible Node.js web application framework.

The MVC design pattern is particularly popular in web development due to its efficiency and maintainability. It separates an application's concerns; meaning changes to one component (Model, View, or Controller) can be made with minimal impact on the others. This makes development, debugging, and testing much easier and more efficient.

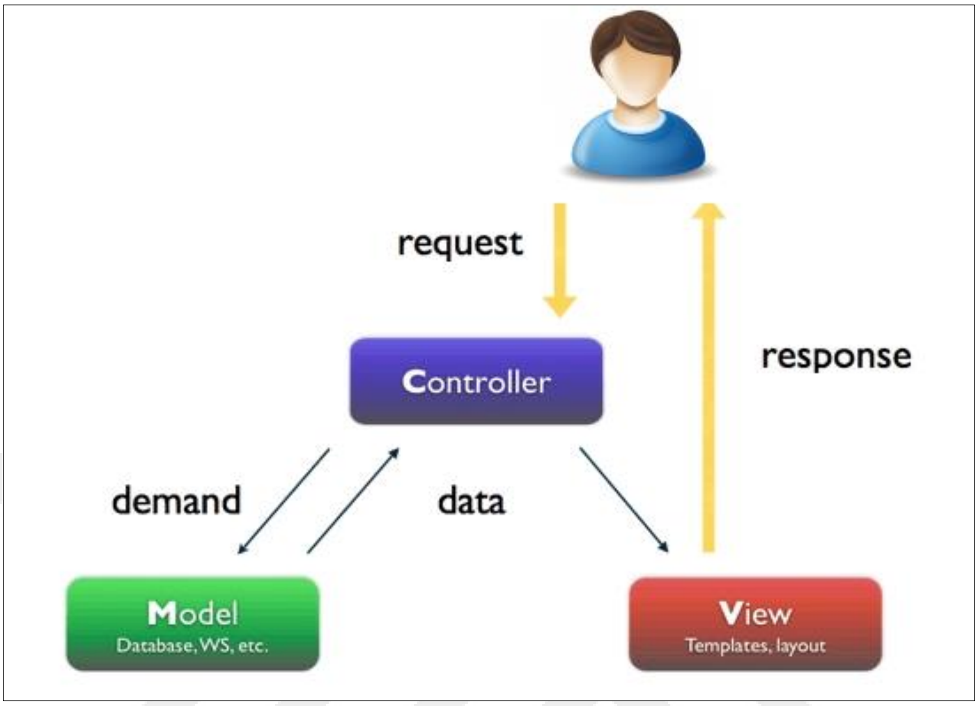


Figure 4.1: MVC Pattern Architecture.

4.1.2 Frameworks and Technology justification

a. Front-End Framework: React.js is a widely adopted JavaScript library, known for building rich user interfaces, particularly for single-page applications. By breaking down the application's UI into components, React.js supports code reusability and maintainability, especially in large codebases. React's virtual DOM promotes efficient updates and rendering, thus improving the performance of the application. For our financial analysis tool, we are using React.js to create an engaging and interactive UI for end-users [77].

Figure 4.2: React Library Logo.

b. Back-End Framework: NET 6 is the latest version of the NET framework, developed by Microsoft. It is a cross-platform framework that allows developers to build a wide range of C-sharp applications, including web applications, desktop applications, mobile apps, and cloud-based services. .NET 6 introduces several new features and improvements to enhance developer productivity and application performance [78].

C# (pronounced) is a modern, object-oriented programming language developed by Microsoft. It is one of the primary languages used for developing applications on the NET platform. C# provides a powerful and expressive syntax, strong typing, and a rich set of features for building robust and scalable applications. It supports various programming paradigms, including imperative, declarative, functional, and object-oriented programming. Together, NET 6 and C# form a powerful combination for developing high-performance and scalable applications. With NET 6, developers can leverage the latest features and improvements in the framework, while using C# to write clean and efficient code. The combination of these technologies allows for rapid application development, seamless integration with other .NET components, and access to a vast ecosystem of libraries and tools.

Figure 4.3: Microsoft .Net Logo.

c. Database: The dataset refers to the structured data used in the project for calculations, analysis, and reporting. It could include various data points related to the project, such as capacity, operating costs, production figures, revenue, and other relevant financial metrics. The dataset is typically stored in a database, such as SQL Server, which provides efficient data storage, retrieval, and querying capabilities. In the context of this project, the dataset is managed and accessed using .NET technologies to interact with the underlying database, retrieve the data, and perform calculations and analysis as required by the application.

Figure 4.4: SGL Server.

Combining React.js, .NET, and SQL Server allows us to develop a robust, efficient, and flexible financial analysis tool. This technology stack will enable us to manage complex calculations, handle extensive data, and deliver a seamless and responsive user experience.

4.1.3 Web-Based Refinery DSS Architecture

The architecture of our web-based refinery DSS is a multi-tier system, comprising of the following major components:

a. Client Tier (Front-End): This is the user interface of the web application, where users interact with the system. We are using React.js to build this layer, as it allows us to develop an interactive, component-based UI that can be easily maintained and scaled. This tier is responsible for collecting user inputs, displaying results, and providing overall interaction with the user.

b. Server Tier (Back-End): This tier, developed using .NET 6 and C#, contains the logic of the application. It processes the requests from the front-end, performs calculations, and sends back the responses. This layer consists of Controllers that manage the connection between the front-end and the back-end and also models that handle data manipulation. The server tier is hosted on a web server, allowing for remote access and operation.

c. Data Tier (Database): The data tier is where the application data is stored and retrieved. For this layer, we use SQL Server for its robustness and scalability. The database stores all the data related to the users, their input sheets, and calculation sheets. The server tier interacts with the database to retrieve and store data as needed.

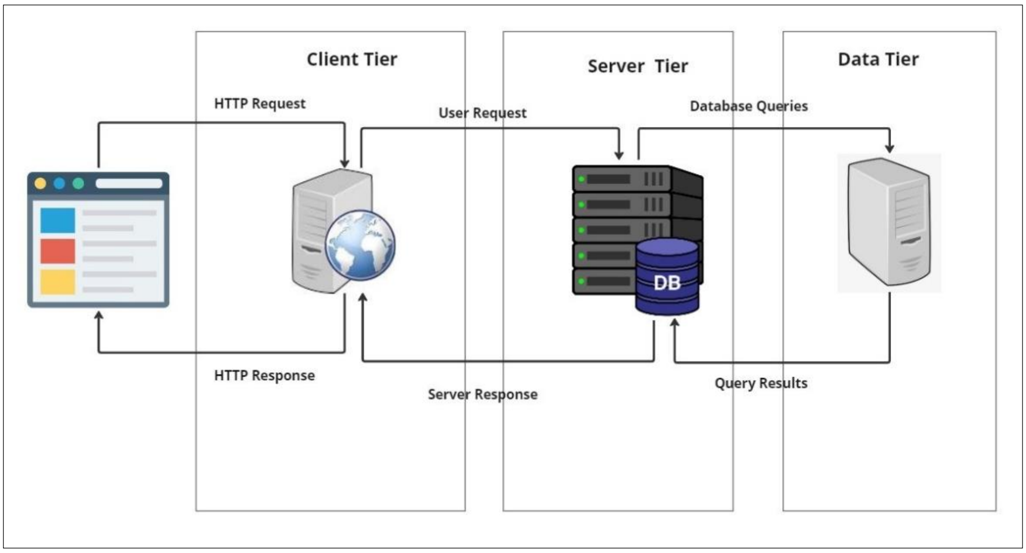


Figure 4.5: Web-Based Refinery DSS Architecture.

In the context of the calculation sheet described, the term "tables" refers not to traditional data tables, but rather to specific columns or sections where various financial calculations are systematically organized and performed. Each "table" represents a distinct financial metric or formula relevant to the company's financial analysis. For instance, Table 1, dealing with 'EQUITY CAPEX' and 'DEBT CAPEX', is concerned with calculating the portions of capital expenditure financed through equity and debt respectively. These tables collectively provide a structured framework for calculating and analyzing key financial aspects such as revenue projections, operating costs, depreciation, loans, and taxes, among others. This structured approach ensures that all critical financial components are meticulously accounted for and enables the company to derive meaningful insights regarding its financial health, investment returns, and future cash flows. By segmenting these complex calculations into discrete "tables", the sheet enhances clarity, facilitates easier understanding and review, and provides a comprehensive view of the financial model in a streamlined and accessible manner.

4.2 USER INTERFACE SHOWCASE

4.2.1 Creating the Input Sheet

The input sheet's creation process involves a series of steps that progressively develop the refinery's economic model, add materials, and create products. These steps aim to capture a comprehensive set of data for further processing and analysis.

a. Refinery Economic Model: The first step involves the user filling out a table representing the refinery's economic model. The user will input data into designated fields in the table to establish the baseline of the refinery's economic model. The web application's user interface is designed to make this step intuitive and straightforward. Users are guided through the process with clear instructions and prompts. Additionally, the system performs real-time data validation to minimize errors and ensure the quality of the data being entered. Table provides a brief description of each variable involved in the input sheet of the refinery's economic model.

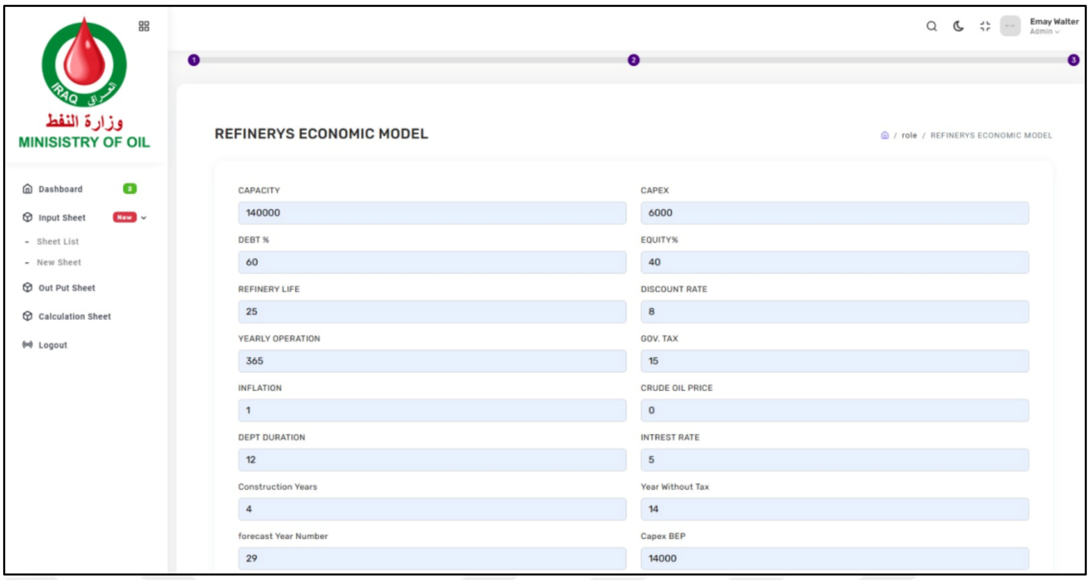


Figure 4.6: Refinery Economic Model Interface.

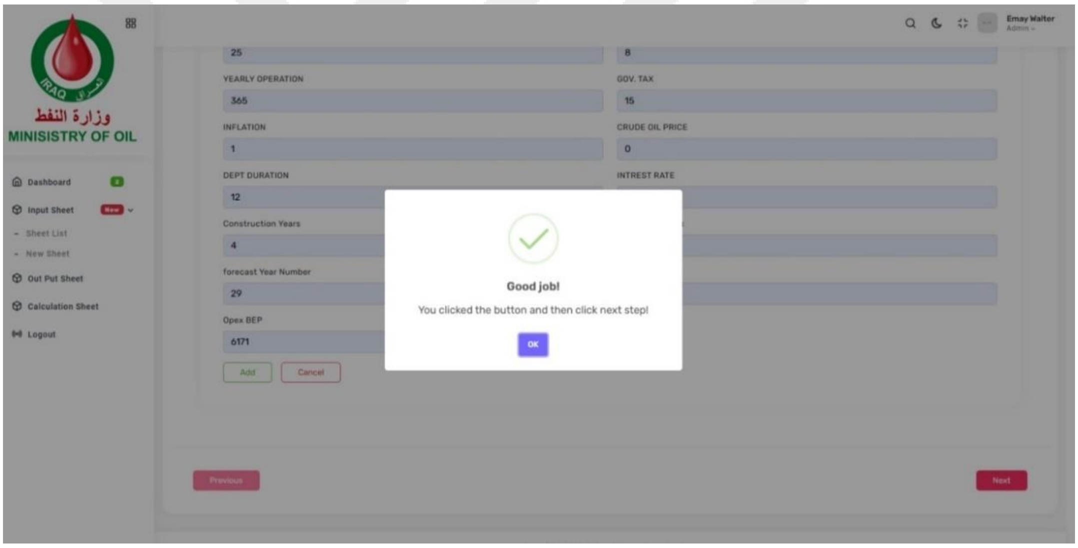


Figure 4.7: Creation and Validation of the Refinery Economic Model.

The development of the Refinery Economic Model introduces a state-of-the-art approach to inputting and analyzing economic parameters. As shown in Figure 4.6, the model offers a comprehensive interface that facilitates easy entry of key economic parameters. Users are provided with fields ranging from 'CAPEX' to 'CRUDE OIL PRICE', ensuring that all crucial variables are covered.

Upon input, the model goes through a stringent validation process. Successful validation, as demonstrated in Figure 4.7, is paramount, as it ensures the accuracy and reliability of the generated data. This validation process not only verifies the appropriateness of the inputted data but also guides users to correct any inconsistencies, thereby maintaining the integrity of the model's outputs.

Table 4.1: The Refinery Economic Model Features.

Variable	Description
Capacity	Refers to the maximum output that the refinery can produce.
DEBT %	Represents the proportion of the total capital that is financed through debt.
Refinery Life	The expected operational lifespan of the refinery.
Yearly Operation	The number of days or hours the refinery operates in a year.
Inflation	The rate at which the general level of prices for goods and services is rising, eroding purchasing power.
Debt Duration	The length of time it will take to pay off the debt under agreed terms.
Construction Years	The time it takes to build and make the refinery fully operational.
Forecast Year Numbers	The number of years for which financial projections are made.
CAPEX (Capital Expenditure)	Funds used by the refinery to acquire, upgrade, and maintain physical assets.
EQUITY %	The portion of the total capital that is financed through the company's own equity.
Discount Rate	The interest rate used in discounted cash flow (DCF) analysis to determine the present value of future cash flows.
GOV. TAX (Government Tax)	The amount of tax levied by the government on the refinery's income, sales, or property.
Crude Oil Price	The cost per barrel of crude oil at a given time.
Interest Rate	The amount charged, expressed as a percentage of principal, by a lender to a borrower for the use of assets.
Year without Tax	The period during which the refinery is exempted from paying taxes.
CAPEX BEP (Capital Expenditure Break-Even Point)	The point at which the income from an investment equals the initial capital outlay.

b. Create Material: After providing the economic model data, the user moves on to the input of raw material and operating costs. This process involves specifying the various materials essential to the refinery's operation. Each material has a set of properties that need to be defined:

Material Name: This could be Crude oil, Natural Gas, Steam, Power, Cooling water, Sulphuric Acid, or any other material integral to the refinery's operations (See Table 4.2).
Price ($/ton): The price per ton of the specific material.
Capacity (ton/d): The amount of the specific material used per day.
The materials table will have these columns: Material Name, Price ($/ton), and Capacity (ton/d). The user will input the price and capacity for each listed material. The interface is designed to be user-friendly, providing easy-to-fill forms and offering real-time validation to avoid possible data input errors.

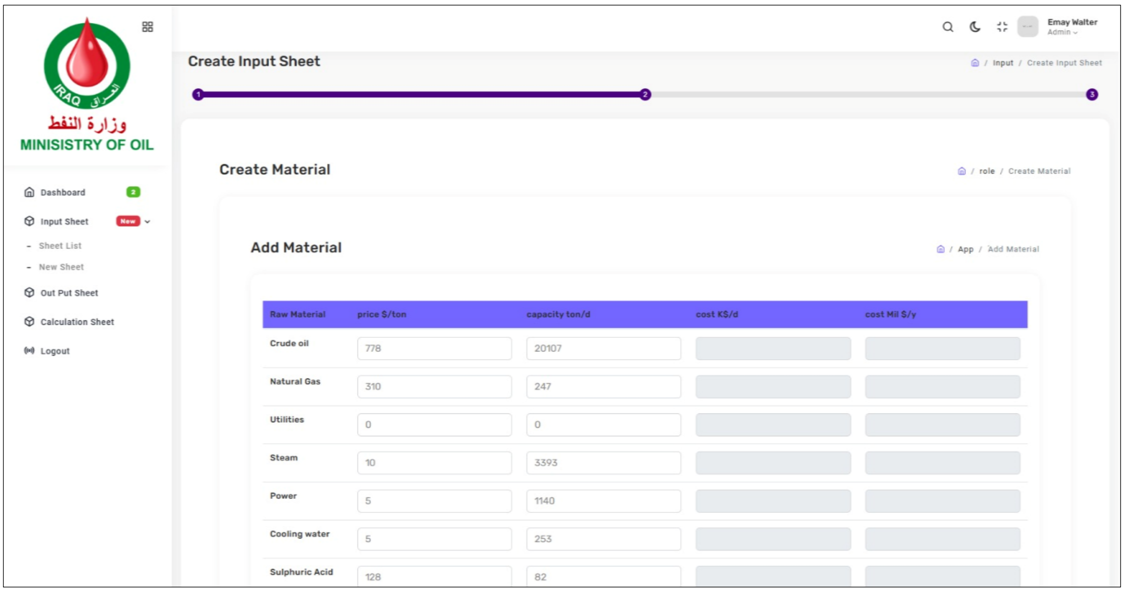


Figure 4.8: Create Material Row Interface.

In Figure 4.8, the interface shows a section dedicated to adding materials. Users can input various details such as the material name, its production cost, capacity level, cost in KD, and cost in KD/y. It provides a clean and structured way to input information about different materials.
Once the user has inputted the necessary data, the system will automatically calculate the cost per day and cost per year for each material. These calculations provide valuable insights into the refinery's day-to-day and annual operating costs. By understanding these costs, decision-makers can better plan their budgets, identify potential areas for cost reduction, and ensure the refinery's economic viability.
The "Gross Operating Cost" is automatically calculated by the system after all material cost data have been entered by summing up the "Cost (Mil $/y)" for all the listed materials.

This computed "Gross Operating Cost" provides valuable insights into the total expenditure involved in operating the refinery, considering all the listed materials. It helps stakeholders understand the overall financial implications of the refinery's operations and plays a crucial role in assessing its profitability.

By displaying the "Gross Operating Cost" at the end of the table, users can easily assess the cumulative cost impact of all materials and make informed decisions regarding operational efficiency, cost optimization, and financial planning.

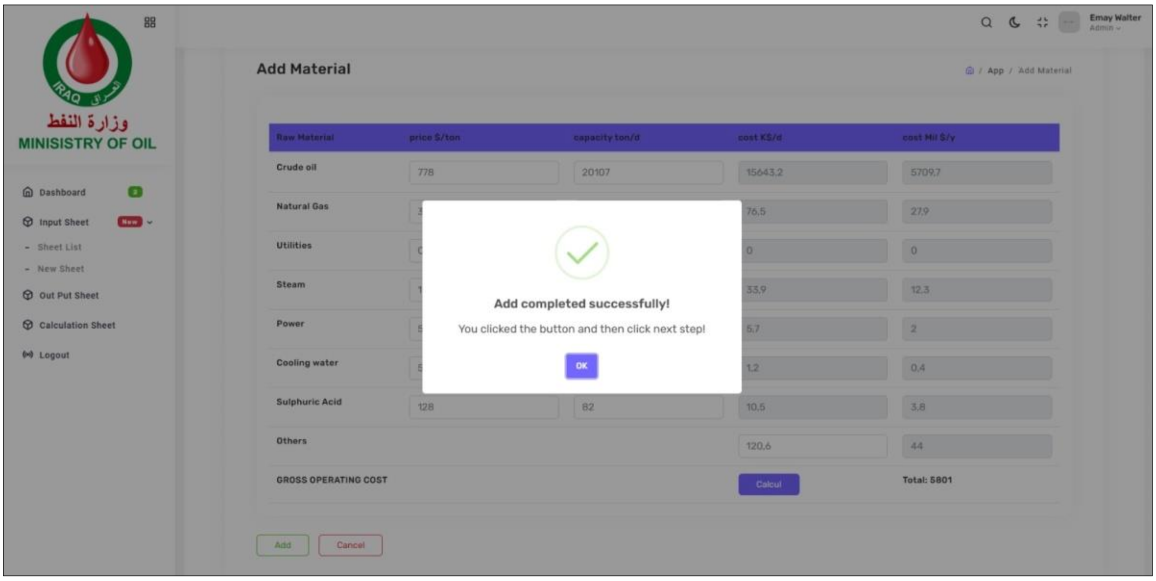


Figure 4.9: Creation and Validation of Material Row.

Figure 4.9 illustrates the subsequent step after adding a material. It provides a confirmation pop-up window notifying the user that the material has been added successfully, guiding them to proceed to the next step.

Table 4.2: Create Material Features.

Material	Description
Crude Oil	The raw material from which various petroleum products are derived in a refinery.
Natural Gas	A naturally occurring hydrocarbon gas mixture used in a refinery for various purposes, including as a fuel and a component in various chemical reactions.
Utilities	Services required for the refinery's operations such as water supply, waste management, etc.
Steam	Used in several refinery processes, including driving turbines and as a heat source.
Power	The electricity used to run the machinery and equipment in the refinery.
Cooling Water	Used in the cooling towers to remove excess heat from the refinery processes.
Sulphuric Acid	A chemical reagent used in a variety of refining processes.
Cross Operating Cost	Total annual operating cost of the refinery.

c. Create Product: In this step, users will focus on the refinery's production aspect, specifying each product's output capacity and price. The products could include LPG, different grades of Gasoline, Kerosene, Gasoil, Heavy Diesel, Fuel Oil, Vacuum Residue, Asphalt, Sulphur, or any other products that the refinery produces (See Table 4.3).

The product table consists of the following columns: Product Name, Price ($/ton), and Capacity (ton/d). The user will enter the product price per ton and the output capacity per day for each listed product. The system offers an easy-to-use interface with form validation features to ensure data accuracy.

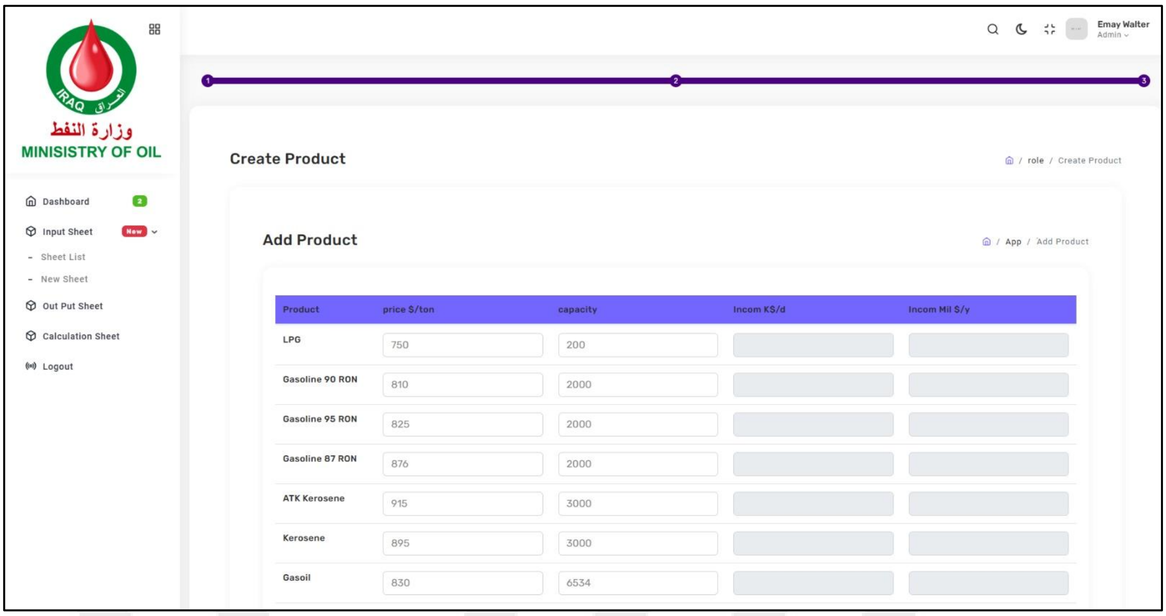


Figure 4.10: Create Product Interface.

In Figure 4.10, the focus shifts to product creation. Similar to the material row interface, users can input details related to a product such as its name, price in Din, capacity, income in KD, and income in KD/y.

After the user provides these data points, the system will automatically calculate the daily income and yearly income for each product. These calculations help to determine the revenue generated by each product on a daily and yearly basis. By understanding these figures, stakeholders can make informed decisions about their production planning, pricing strategy, and market positioning.

The "Gross Production Revenue" is an essential figure representing the total annual revenue from all the refinery's products. This is calculated by summing up the "Income (Mil $/y)" for all listed products. This computed Gross Production Revenue is a vital piece of information for stakeholders. It provides an overarching view of the expected annual income from the refinery's total production, serving as a cornerstone for further financial analysis and decision-making. As soon as the required data are input, the system computes these values and displays them in a clear, easy-to-understand format. This approach ensures users can quickly gain insight into their production revenue dynamics without the need for manual computation.

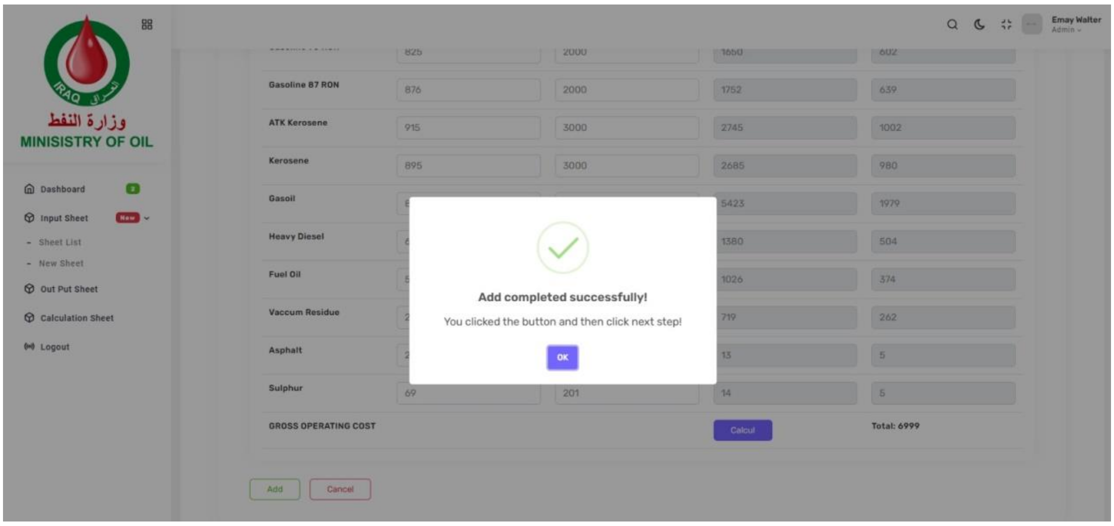


Figure 4.11: Creation and Validation of Product Row.

Figure 4.11 presents the validation step for product addition. A confirmation window appears to acknowledge the successful addition of the product, prompting users to continue to the subsequent stage.

Table 4.3: Create Product Features.

Product	Description
LPG (Liquefied Petroleum Gas)	A portable, clean and efficient energy source which is readily available to consumers around the world. It’s used in hundreds of applications, such as cooking and heating.
Gasoline 90 RON	Regular gasoline with a Research Octane Number (RON) of 90. Used as fuel for motor vehicles.
Gasoline 95 RON	Premium gasoline with a RON of 95. Higher octane rating can provide greater engine performance and lower fuel consumption.
Gasoline 87 RON	Regular gasoline with a Research Octane Number (RON) of 87. It is the standard fuel for most motor vehicles.
ATK kerosene	Aviation turbine fuel (ATF) or Jet fuel. It’s a type of aviation fuel designed for use in aircraft powered by gas-turbine engines.
Kerosene	A type of fuel used in jet engines and tractors, some lamps, stoves, and heaters.
Gasoil	Also known as diesel oil, used in diesel engines, which can be used in cars, trucks, and buses, among others.
Cross Production Revenue	The total annual revenue from all the refinery's products

4.2.2 The Output Sheets

The output sheet displays the results of the economic modelling based on the inputs provided in the input sheet and the calculation sheet.

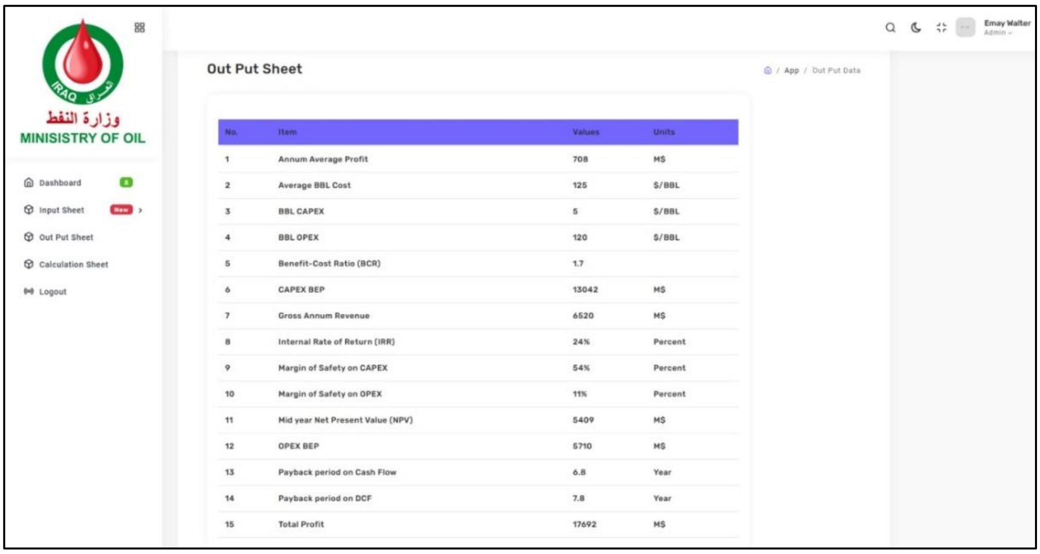


Figure 4.12: Output Sheet Interface.

In Figure 4.12, the interface displays an output sheet that consolidates various financial metrics and values. Metrics like the annual average profit, average unit cost, gross annual revenue, and others provide a comprehensive overview of the financial health and performance of the operations.

4.2.3 Sheet List

The Sheet List Interface in Figure displays a list of all the created sheets. Each sheet in the list has the following features:

a. Number of Capacity: This indicates the production capacity associated with the sheet.

b. Cross Operating Cost: It shows the total operating cost for the specific sheet.

c. Cross Production: This represents the total production output for the sheet.

d. Revenue: It displays the total revenue generated by the sheet.

For each sheet in the list, there are four buttons available:

a. Edit (Blue Color): Clicking on this button allows you to edit the content or properties of the sheet. It opens an editing interface for the selected sheet.

b. Delete (Red Color): This button is used to delete the selected sheet. It removes the sheet from the list.

c. Select (Green Color): Clicking on this button selects the sheet, indicating that it is currently active or in focus.

d. Calculation (Green Color): This button initiates the calculation process for the selected sheet. It triggers the calculations based on the inputs and formulas within the sheet to update the relevant values and results.

The Sheet List Interface provides a convenient overview of all the sheets in the system, allowing users to manage, edit, delete, and perform calculations on each sheet as needed.

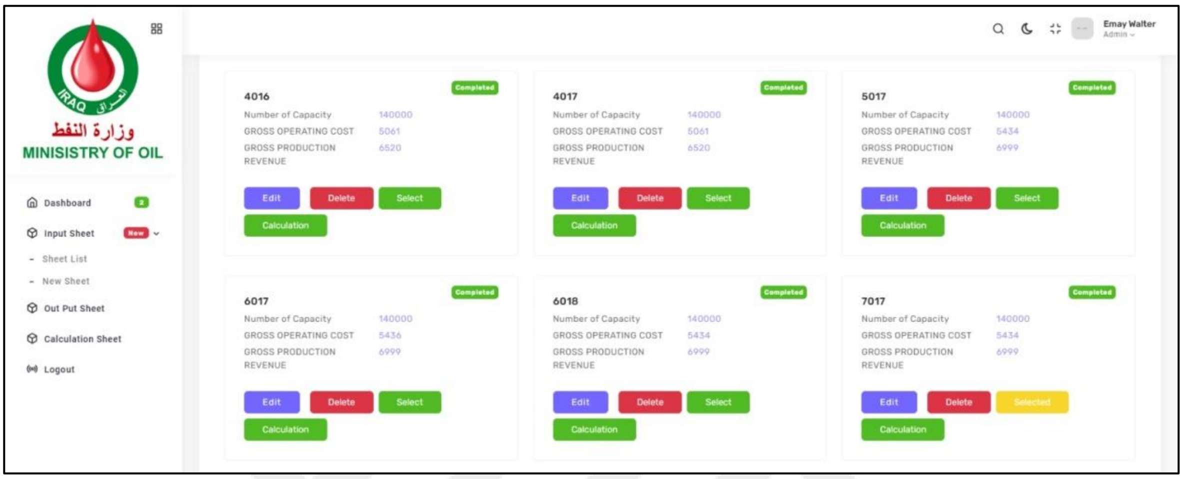


Figure 4.13: Sheet List Interface.

Figure 4.13 showcases an interface where users can view a list of sheets. Each sheet appears as a card containing details like number of capacities, gross production cost, estimated operating cost, and estimated production. Users also have the option to calculate, edit, delete, or select a sheet.

4.2.4 Dashboard

4.2.4.1 Discount impact

In Figure 4.6 of the Refinery Economic Model, we can observe a combination of bar plots and curves representing various aspects of the project's cash flows and their discounted values. The figure provides valuable insights into the financial performance of the refinery project. Here is a description of the different components:

a. Blue Bar Plot: Represents the net cash flow for each year of the project. It shows the positive or negative cash inflow/outflow in each specific year.

b. Pink Bar Plot: Represents the net cash flow for each year of the project, considering the impact of discounting. It reflects the value of cash flows adjusted for the time value of money, using the specified discount rate.

c. Purple Curve: Represents the cumulative net cash flow over time. It shows the total net cash flow accumulated from the start of the project until each specific year. The curve helps assess the overall financial progress of the project.
d. Green Curve: Represents the cumulative net cash flow over time, taking into account the impact of discounting. It considers the discounted value of cash flows and provides insights into the cumulative financial performance of the project, considering the time value of money.

The figure helps visualize the cash flow patterns, both in nominal terms and after applying discounting. It allows for a comprehensive understanding of the project's financial dynamics, including the timing and magnitude of cash flows. This information is crucial for evaluating the project's financial feasibility, profitability, and potential risks.

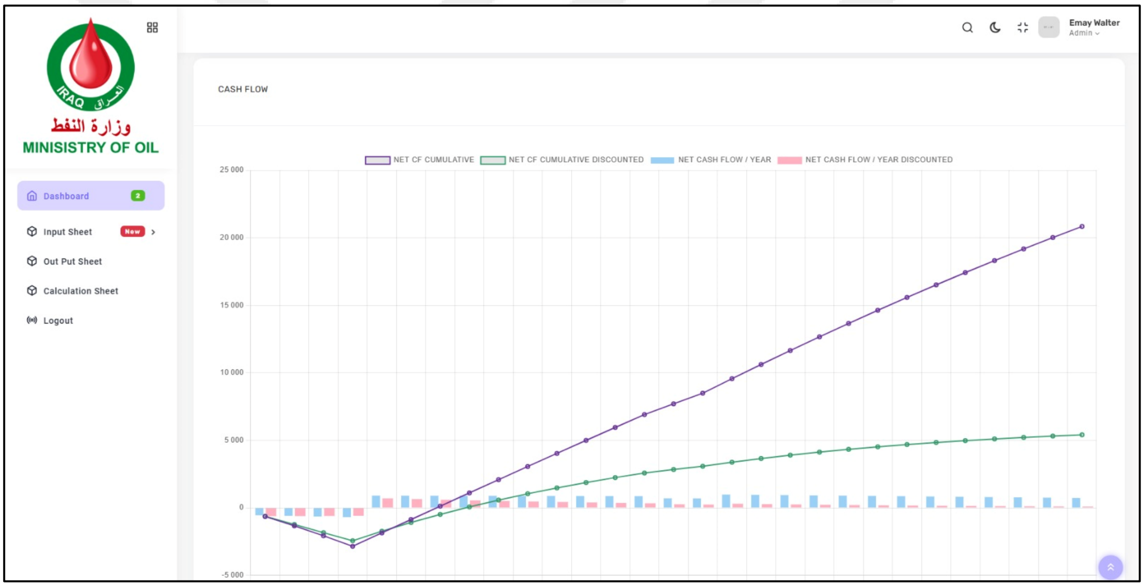


Figure 4.14: Discount Impact Interface.

In Figure 4.14, the interface presents a graphical representation of cash flow against different discounting factors. The chart provides insights into how the cash flow behaves under different discounting scenarios, aiding in financial forecasting and decision-making.

4.2.4.2 Cash flow

In the Figure 4.9, we can observe the financial components of a refinery economic model over a span of 29 years. By analyzing this figure, researchers can evaluate the refinery's profitability, and the impact of equity investments, operating expenses, debt payments, and taxes on its financial performance. It helps assess the project's viability and financial sustainability. The blue colour represents equity-related aspects, such as equity capital expenditures and revenue. The purple colour represents operating expenses, while the dark purple represents debt payments. The black colour represents tax payments.

This figure contributes to a comprehensive understanding of the refinery's financial dynamics and aids in decision-making and financial analysis. Here is a description of the figure.

a. Equity CAPEX: The blue bars represent the equity capital expenditures for each year of the project. They show the amount invested from equity sources in the refinery.
b. Revenue: The blue line represents the revenue generated by the refinery over the years. It starts from year 5 onwards, with specific values mentioned for each year.
c. OPEX: The purple bars represent the operating expenses (OPEX) incurred by the refinery. The values for each year are mentioned on the axis.
d. Debt Payment: The dark purple bars represent the payments made towards debt obligations. The amounts decrease over time, indicating the repayment of the debt.
e. Tax: The black bars represent the tax payments made by the refinery. The values decrease gradually over the years.

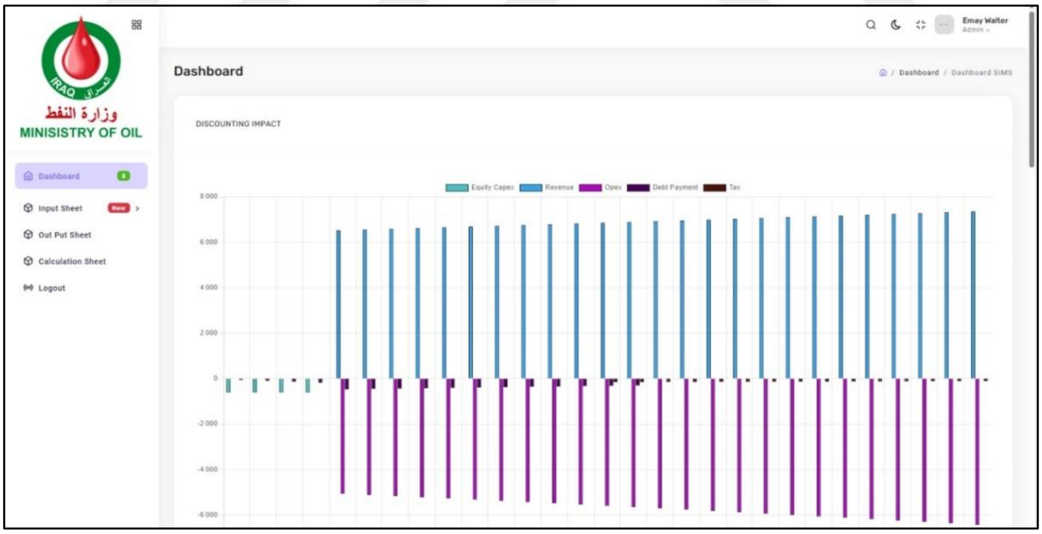
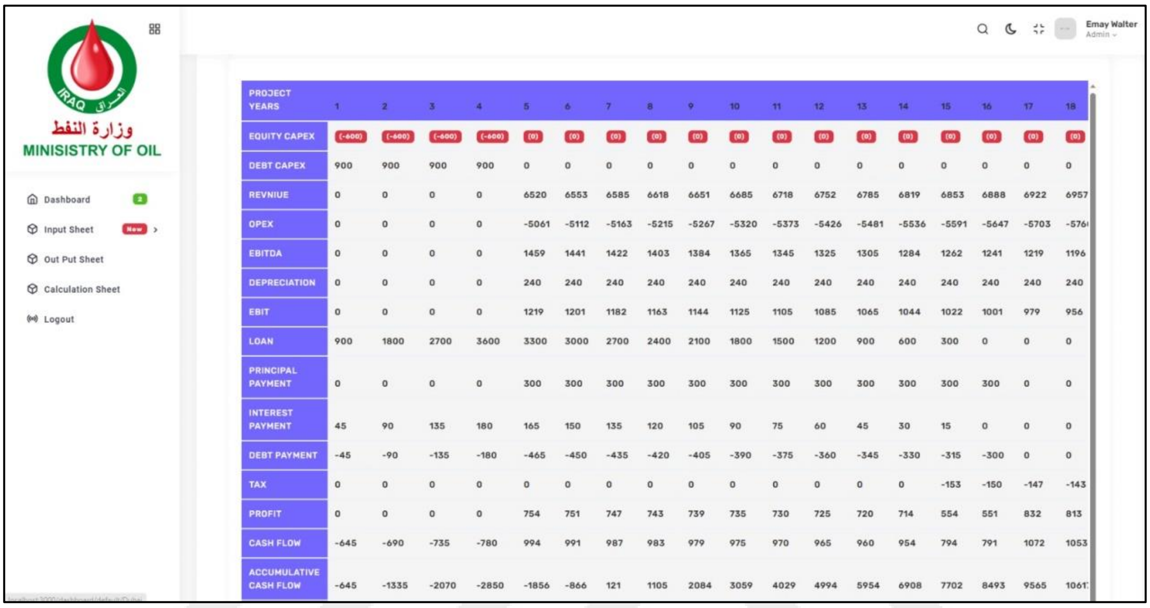


Figure 4.15: Discount Impact Interface.

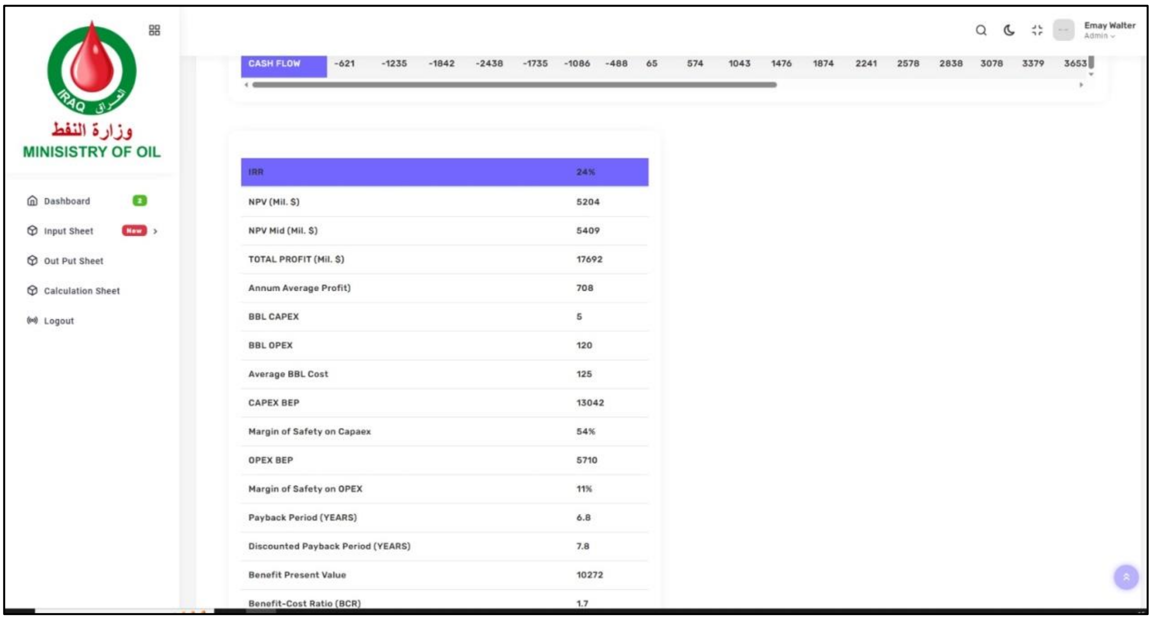
4.3 RESULTS

The calculation sheet provides a comprehensive analysis of the financial aspects of a refinery project. As we talk in the chapter 3 section 3.3.2 the calculation sheet contains for tables illustrated in the Figures



PROJECT YEARS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
EQUITY CAPEX	(-600)	(-600)	(-600)	(-600)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
DEBT CAPEX	900	900	900	900	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REVNIUE	0	0	0	0	6520	6553	6585	6618	6651	6685	6718	6752	6785	6819	6853	6888	6922	6957
OPEX	0	0	0	0	-5061	-5112	-5163	-5215	-5267	-5320	-5373	-5426	-5481	-5536	-5591	-5647	-5703	-576
EBITDA	0	0	0	0	1459	1441	1422	1403	1384	1365	1345	1325	1305	1284	1262	1241	1219	1196
DEPRECIATION	0	0	0	0	240	240	240	240	240	240	240	240	240	240	240	240	240	240
EBIT	0	0	0	0	1219	1201	1182	1163	1144	1125	1105	1085	1065	1044	1022	1001	979	956
LOAN	900	1800	2700	3600	3300	3000	2700	2400	2100	1800	1500	1200	900	600	300	0	0	0
PRINCIPAL PAYMENT	0	0	0	0	300	300	300	300	300	300	300	300	300	300	300	300	0	0
INTEREST PAYMENT	45	90	135	180	165	150	135	120	105	90	75	60	45	30	15	0	0	0
DEBT PAYMENT	-45	-90	-135	-180	-465	-450	-435	-420	-405	-390	-375	-360	-345	-330	-315	-300	0	0
TAX	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-153	-150	-147	-143
PROFIT	0	0	0	0	754	751	747	743	739	735	730	725	720	714	554	551	832	813
CASH FLOW	-645	-690	-735	-780	994	991	987	983	979	975	970	965	960	954	794	791	1072	1053
ACCUMULATIVE CASH FLOW	-645	-1335	-2070	-2850	-1856	-866	121	1105	2084	3059	4029	4994	5954	6908	7702	8493	9565	1061

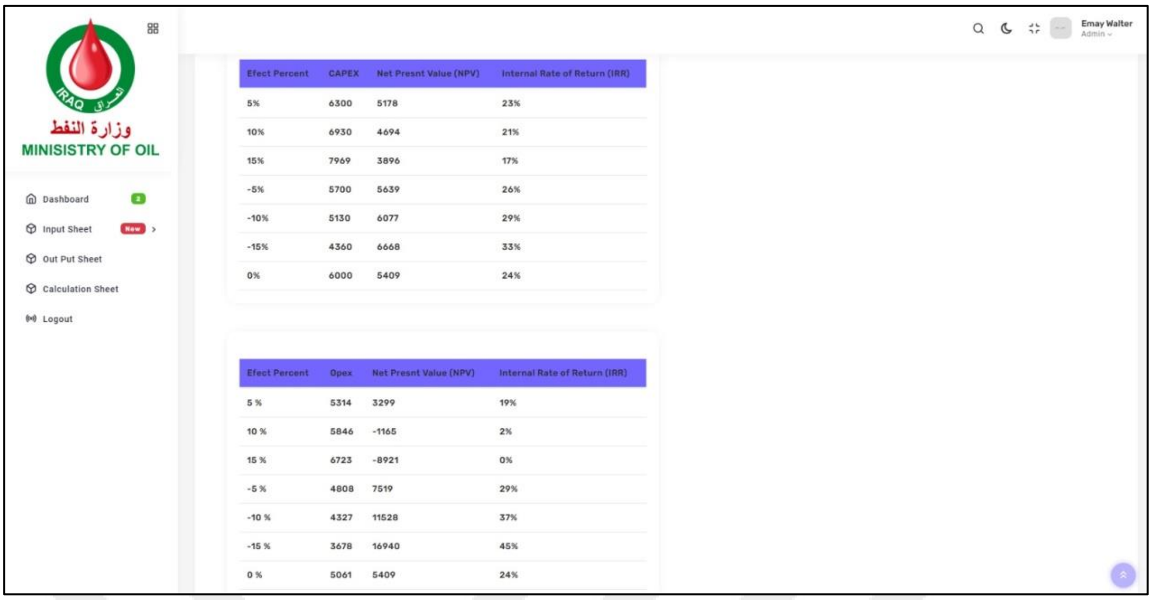
Figure 4.16: Table 1 Interface.



CASH FLOW	-621	-1235	-1842	-2438	-1735	-1086	-488	65	574	1043	1476	1874	2241	2578	2838	3078	3379	3653

IRR	24%
NPV (Mil. $)	5204
NPV Mid (Mil. $)	5409
TOTAL PROFIT (Mil. $)	17692
Annum Average Profit	708
BBL CAPEX	5
BBL OPEX	120
Average BBL Cost	125
CAPEX BEP	13042
Margin of Safety on Capaex	54%
OPEX BEP	5710
Margin of Safety on OPEX	11%
Payback Period (YEARS)	6.8
Discounted Payback Period (YEARS)	7.8
Benefit Present Value	10272
Benefit-Cost Ratio (BCR)	1.7

Figure 4.17: Table 2 Interface.



Efect Percent	CAPEX	Net Presnt Value (NPV)	Internal Rate of Return (IRR)
5%	6300	5178	23%
10%	6930	4694	21%
15%	7969	3896	17%
-5%	5700	5639	26%
-10%	5130	6077	29%
-15%	4360	6668	33%
0%	6000	5409	24%

Efect Percent	Opex	Net Presnt Value (NPV)	Internal Rate of Return (IRR)
5 %	5314	3299	19%
10 %	5846	-1165	2%
15 %	6723	-8921	0%
-5 %	4808	7519	29%
-10 %	4327	11528	37%
-15 %	3678	16940	45%
0 %	5061	5409	24%

Figure 4.18: CAPEX and OPEX Sensitivity Analysis Tables Interface.

4.3.1 Opex Sensitivity Analysis

The OPEX Analysis provides insights into the impact of different percentage variations in the OPEX (Operating Expenses) on the Net Present Value (NPV) and Internal Rate of Return (IRR) of a project. Here is a description of the two bar plot figures:

Net Present Value (NPV) / OPEX: The percentage variations in the OPEX are displayed on the x-axis. The NPV (in million dollars) is represented on the y-axis. Each blue bar represents the NPV associated with a positive or negative percentage variation in the OPEX. The height of the bars indicates the magnitude of the NPV. This figure allows for a comparison of the NPV values corresponding to different percentage variations in the OPEX. Positive NPV values indicate profitability, while negative NPV values indicate potential losses. The figure helps assess the impact of OPEX variations on the project's financial performance.

Internal Rate of Return (IRR) / OPEX: The percentage variations in the OPEX are displayed on the x-axis. The IRR (in percentage) is represented on the y-axis. Each blue bar represents the IRR associated with a positive or negative percentage variation in the OPEX. The height of the bars indicates the magnitude of the IRR. This figure allows for a comparison of the IRR values corresponding to different percentage variations in the OPEX. Positive IRR values indicate profitability and financial feasibility, while negative IRR values indicate potential losses. The figure helps assess the project's financial viability under varying OPEX scenarios.

By examining these bar plot figures, analysts and researchers can evaluate the sensitivity of the project's NPV and IRR to changes in the OPEX. It provides a visual representation of the relationship between OPEX variations and the financial performance indicators. This information aids decision-making and risk analysis, allowing stakeholders to determine the optimal level of OPEX that maximizes the project's NPV and IRR.

Figure 4.19: OPEX Sensitivity Analysis Interface.

In Figure 4.19, the OPEX (Operating Expenditure) Sensitivity Analysis interface from the Ministry of Oil is depicted. The main dashboard at the top displays a graph indicating a specific trend, although the labels are not distinctly visible. Below the primary graph, there are two bar charts presenting the OPEX Sensitivity Analysis. The chart on the left represents the 'Net Present Value (NPV) vs. OPEX %, indicating how the net present value is affected by different percentages of OPEX. The chart on the right depicts the 'Internal Rate of Return (IRR) vs. OPEX %,' showcasing how varying OPEX percentages impact the internal rate of return.

4.3.2 Capex Sensitivity Analysis

The CAPEX Analysis provides insights into the impact of different percentage variations in the CAPEX (Capital Expenditure) on the Net Present Value (NPV) and Internal Rate of Return (IRR) of a project. Here is a description of the two bar plot figures (See Figure 4.8): Net Present Value (NPV) / CAPEX: The percentage variations in the CAPEX are displayed on the x-axis. The NPV (in million dollars) is represented on the y-axis. Each blue bar represents the NPV associated with a specific percentage variation in the CAPEX. The height of the bars indicates the magnitude of the NPV.

This figure allows for a comparison of the NPV values corresponding to different percentage variations in the CAPEX. It helps identify the impact of increasing or decreasing the CAPEX on the project's NPV.

Internal Rate of Return (IRR) / CAPEX: The percentage variations in the CAPEX are displayed on the x-axis. The IRR (in percentage) is represented on the y-axis. Each blue bar represents the IRR associated with a specific percentage variation in the CAPEX. The height of the bars indicates the magnitude of the IRR. This figure allows for a comparison of the IRR values corresponding to different percentage variations in the CAPEX. It helps assess the project's profitability and financial feasibility under varying CAPEX scenarios.

By examining these bar plot figures, analysts and researchers can evaluate the sensitivity of the project's NPV and IRR to changes in the CAPEX. It provides a visual representation of the relationship between CAPEX variations and the financial performance indicators. This information aids decision-making and risk analysis, allowing stakeholders to determine the optimal level of CAPEX that maximizes the project's NPV and IRR.

Figure 4.20: CAPEX Sensitivity Analysis Interface.

In Figure 4.20, the CAPEX (Capital Expenditure) Sensitivity Analysis interface is shown. Similar to the previous figure, two bar charts are presented. The leftmost chart represents 'Net Present Value (NPV) vs. CAPEX %,' illustrating the relationship between the net present value and different CAPEX percentages. The right chart provides insights into the

'Internal Rate of Return (IRR) vs. CAPEX %,' explaining how IRR is influenced by various CAPEX percentages. Both charts are essential for understanding the sensitivity of financial metrics to changes in capital expenditures.

4.4 COMPARATIVE STUDY

In the realm of decision-making and optimization within various industries, the development and implementation of Decision Support Systems (DSS) have become pivotal. The abstract provided earlier delineates the creation of a DSS for the refinery industry, utilizing .NET 6 and C# for backend operations and ReactJS for frontend user interface development. This system aims to streamline decision-making by automating data analysis and providing real-time access to crucial data, thereby enhancing operational efficiency and fostering informed, strategic decision-making.

Comparatively, the first study [79], explores the challenges faced by post-industrial cities experiencing population decline and socioeconomic transformations. The research aims to identify and classify measures against urban decline by analyzing international cases of shrinking cities where successful measures have been implemented. The study prioritizes alternatives using an Analytic Hierarchy Process and emphasizes sustainability in its criteria and measures, showcasing a structured approach to addressing urban decline through methodical analysis and prioritization of alternatives.

The second study [80], navigates the complexities of the residential market, particularly focusing on high-performance residential buildings and the intricate decision-making processes involved in optimal retrofitting. The study introduces a performance-oriented decision support workflow for a multifamily apartment block, employing automated parametric energy simulation and multiple-criteria decision analysis to explore and determine optimal retrofit alternatives. This approach seeks to provide architects and residence owners with a tool to make informed decisions about performance-based retrofitting by comparing the energy and economic performance of alternatives.

In the third study [81], the focus shifts to supply chain risk management within the Indian petroleum supply chain. The paper develops a DSS to assist supply chain risk managers in selecting suitable risk management strategies and expedite the implementation of corresponding risk management enablers. The system is built by integrating heterogeneous techniques, including a systematic review approach, correspondence analysis, and a rulebased fuzzy inference system, demonstrating a multifaceted approach to managing supply chain risks by recommending effective risk mitigation strategies and corresponding enablers. Lastly, the fourth study [82], delves into predictive maintenance within the industry 4.0 paradigm, presenting a prototype DSS that utilizes machine learning and artificial intelligence algorithms to report and correct deviations from optimal processes. The system, developed using open-source R packages, is validated through a case study, emphasizing the benefits of employing open-source predictive maintenance tools for small and medium enterprises, such as cost savings and increased accuracy.

In synthesizing these studies, it is evident that the development and implementation of Decision Support Systems span various industries and applications, from urban development and building retrofitting to supply chain management and predictive maintenance. Each study, while rooted in different contexts and objectives, underscores the pivotal role of DSS in enhancing decision-making processes by providing structured, analytical, and data-driven approaches to navigating complex challenges and scenarios. The comparative analysis of these studies alongside the initial abstract provides a rich tapestry of insights and methodologies that can potentially enhance the development and application of the DSS in the refinery industry, particularly in harnessing advanced technologies and methodologies to navigate its unique challenges and optimize decision-making processes.

Table 4.4: Comparison Studies.

Criteria	Study [79]	Study [80]	Study [81]	Study [82]	Proposed DSS Application
Focus Industry	Post-Industrial Cities	Residential Building Retrofit	Indian Petroleum Supply Chain	Industry 4.0 - General Manufacturing	Refinery Industry
Methods/Techniques	Analytic Hierarchy Process	Parametric Energy Simulation	Systematic Review, Correspondence Analysis, Fuzzy Inference System	Machine Learning, AI	Data Analysis Automation
Objectives	Addressing Urban Decline	Optimal Retrofit Decisions	Risk Management Strategy Selection	Predictive Maintenance	Streamline Decision-making
Tools/Platforms	Not specified	Not specified	Not specified	Open-source R packages	.NET 6, C#, ReactJS
Primary Benefits	Structured Approach to Urban Issues	Energy & Economic Performance Insights	Risk Mitigation Recommendations	Cost savings, Increased Accuracy	Real-time Access to Data, Enhanced Operational Efficiency

5. CONCLUSION

5.1 CONCLUSION

In today's fast-paced and complex business environment, organizations face numerous challenges in making informed decisions. To navigate this complexity and optimize decision-making, the development of DSS has become crucial. DSS leverages advanced technologies and data management techniques to provide decision-makers with valuable insights, analysis, and simulation capabilities. By harnessing the power of data, DSS empowers organizations to make strategic and data-driven decisions that drive growth, efficiency, and competitiveness.

a. Importance of DSS: In the contemporary business landscape, Decision Support Systems (DSS) are indispensable for making data-driven, strategic decisions amidst complexities.
b. Project Objective: Our project centered on designing a DSS tailor-made for the refinery industry, aiming to aid in evaluating factors like capacity, costs, production, and revenue.
c. Development Approach: The DSS creation followed a systematic path, from gathering requirements to deployment, ensuring the system was holistic and industry-specific.
d. Data Transition: A significant milestone was the conversion of Excel-based models into an automated system, leading to better data utilization.
e. Technological Backbone: Advanced technologies like .NET 6 and C# formed the core of backend operations, making data handling and complex calculations more efficient.
f. User-Centric Frontend: ReactJS was chosen for frontend development to ensure a seamless and engaging user experience, enabling easy data visualization and analysis.
g. Benefits and Significance: The DSS fortifies decision-making in the refinery sector, allowing for insightful examinations of operational facets and promoting informed strategic decisions.
h. Operational Efficiency: With this DSS, refineries can achieve enhanced efficiency, optimized resource usage, and gain a competitive advantage.
i. Automation Advantages: Transitioning from manual Excel models to an automated DSS led to considerable time and cost savings, streamlining data processing tasks.
j. Strategic Focus: The automation provided by the DSS allows decision-makers to redirect their efforts towards overarching strategic planning and implementation.

5.2 FUTURE WORK

a. AI and ML Integration:

a. Enhance predictive analytics to anticipate trends and risks.

b. Automate complex decision-making processes for more data-driven recommendations.

b. Scalability & Adaptability:

a. Explore DSS applicability to diverse sectors like manufacturing, logistics, and healthcare.

b. Adapt to industry-specific needs and regulatory compliance.

c. Enhanced User Interaction:

a. Incorporate natural language processing for intuitive user queries.

b. Use VR or AR for immersive data visualization experiences.

d. Global Supply Chain Management:

a. Integrate global market data for comprehensive analysis.

b. Consider international regulations for a globalized business approach.

e. Cybersecurity & Data Privacy:

a. Strengthen cybersecurity measures against potential threats.

b. Ensure compliance with data protection regulations and continuous system monitoring.

In summary, the future enhancements of the DSS span from technological integration and user experience optimization to broader applicability, global considerations, and cybersecurity fortifications.

REFERENCES

[1] McKinsey & Company. (2021). Global oil outlook to 2040. Energy Insights. Retrieved from,https://www.mckinsey.com/~/media/McKinsey/Industries/Oil%20and%20Gas/Our%20Insights/Global%20oil%20outlook%20to%202040/Global-oil-outlook-to-2040.ashx.

[2] C. Ding, A. Ferro, T. Fitzgibbon, and P. Szabat, "Refining in the energy transition through 2040," McKinsey & Company, 2022. [Online]. Available: https://www.mckinsey.com/industries/oil-and-gas/our-insights/refining-in-the-energy-transition-through-2040.

[3] C. Ding, A. Ferro, T. Fitzgibbon, and P. Szabat, "Refining in the energy transition through 2040," McKinsey & Company, 2022. [Online]. Available: https://www.mckinsey.com/industries/oil-and-gas/our-insights/refining-in-the-energy-transition-through-2040.

[4] C. Ding, A. Ferro, T. Fitzgibbon, and P. Szabat, "Refining in the energy transition through 2040," McKinsey & Company, 2022. [Online]. Available: https://www.mckinsey.com/industries/oil-and-gas/our-insights/refining-in-the-energy-transition-through-2040.

[5] Murty, K. G. (2020). Models for Optimum Decision Making. Springer.

[6] Patel, H., Prajapati, D., Mahida, D., & Shah, M. (2020). Transforming petroleum downstream sector through big data: a holistic review. Journal of Petroleum Exploration and Production Technology, 10, 2601-2611.

[7] Jones, D.S.J., Pujadó, P.R. (2015). Petroleum Refinery Planning and Economics. In: Treese, S., Pujadó, P., Jones, D. (eds) Handbook of Petroleum Processing. Springer, Cham. https://doi.org/10.1007/978-3-319-14529-7_28

[8] DataReportal. “Global Digital Overview.” DataReportal – Global Digital Insights, 2022, datareportal.com/global-digital-overview.

[9] Bernard, Carol. “The Excel Spreadsheet and Its Limitations.” Www.captio.com, 19 May 2016, www.captio.com/blog/the-excel-spreadsheet-and-its-limitations.

[10] Phillips-Wren, G., Daly, M., & Burstein, F. (2021). Reconciling business intelligence, analytics and decision support systems: More data, deeper insight. Decision Support Systems, 146, 113560.

[11] Shim, J. P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R., & Carlsson, C. (2002). Past, present, and future of decision support technology. Decision support systems, 33(2), 111-126.

[12] Vercellis, C. (2011). Business intelligence: data mining and optimization for decision making. John Wiley & Sons.

[13] Vohra, R. (2011). Intelligent decision support systems for admission management in higher education institutes. International Journal of Artificial Intelligence & Applications (IJAIA), 2(4).

[14] Jung D, Tran Tuan V, Quoc Tran D, Park M, Park S. Conceptual Framework of an Intelligent Decision Support System for Smart City Disaster Management. Applied Sciences. 2020; 10(2):666. https://doi.org/10.3390/app10020666

[15] Konsynski, B.R. (1983). Model Management in Decision Support Systems. In: Holsapple, C.W., Whinston, A.B. (eds) Data Base Management: Theory and Applications. Nato Advanced Study Institutes Series, vol 98. Springer, Dordrecht. https://doi.org/10.1007/978-94-009-7029-8_7

[16] CFI Team (2023). Decision Support System (DSS) - Overview, Components, Types. Corporate Finance Institute.

[17] Chapter 5 Designing and Evaluating DSS User Interfaces. ScholarWorks at University of Northern Iowa. https://scholarworks.uni.edu/cgi/viewcontent.cgi?filename=6&article=1066&context=facbook&type=additional

[18] Hassan, N. R. (2019). The origins of business analytics and implications for the information systems field. Journal of Business Analytics, 2(2), 118-133.

[19] Power, D. J., Heavin, C., & Keenan, P. (2019). Decision systems redux. Journal of Decision Systems, 28(1), 1-18.

[20] Cunningham, L. (2021). Data Literacy Skills–Why are they so Important for Graduates? What can Business Schools do to Improve the Current Situation?. University of Northumbria at Newcastle (United Kingdom).

[21] Alsahfi, T., Almotairi, M., & Elmasri, R. (2020). A survey on trajectory data warehouse. Spatial Information Research, 28, 53-66.

[22] Nyanga, C., Pansiri, J., & Chatibura, D. (2020). Enhancing competitiveness in the tourism industry through the use of business intelligence: A literature review. Journal of Tourism Futures, 6(2), 139-151.

[23] Indeed editorial Team. “What Is a Decsision Support System? (with Benefits).” Indeed Career Guide, 4 Feb. 2023, www.indeed.com/career-advice/career-development/decision-support-system.

[24] Negash, S. (2004). Business intelligence. Communications of the association for information systems, 13(1), 15.

[25] Naeem, T. (2020). Data Mart et Data Warehouse: Connaître la différence. Astera.

[26] Sinha, T. (2021). Cloud Data Lake vs. Data Warehouse vs. Data Mart. IBM Blog. https://www.ibm.com/cloud/blog/cloud-data-lake-vs-data-warehouse-vs-data-mart.

[27] Ask Dan! about DSS - How can organizations keep data-driven DSS and … (n.d.).DSSResources.COM. http://www.dssresources.com/faq/index.php?action=artikel&id=132

[28] Mansfield, L. A., Nowack, P. J., Kasoar, M., Everitt, R. G., Collins, W. J., & Voulgarakis, A. (2020). Predicting global patterns of long-term climate change from short-term simulations using machine learning. npj Climate and Atmospheric Science, 3, Article number: 44.

[29] MSG. “Designing a Decision Support System User Interface.” Www.managementstudyguide.com,www.managementstudyguide.com/designing-decision-support-system-user-interface.htm.

[30] Airinei, D., & Homocianu, D. (2010). A Strategic DSS Model from Functionalities to User Interface. IBIMA Conference Proceedings.

[31] Samimi, A. (2020). Risk Management in Oil and Gas Refineries. Progress in Chemical and Biochemical Research, 3(2), 140-146.

[32] Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data, 7, Article number: 53

[33] Amaran, S., Sahinidis, N. V., Sharda, B., & Bury, S. J. (2016). Simulation optimization: a review of algorithms and applications. Annals of Operations Research, 240, 351–380

[34] Prabhudesai, S., Yang, L., Asthana, S., Huan, X., Liao, Q. V., & Banovic, N. (2023, March). Understanding Uncertainty: How Lay Decision-makers Perceive and Interpret Uncertainty in Human-AI Decision Making. In Proceedings of the 28th International Conference on Intelligent User Interfaces (pp. 379-396).

[35] Božić, V. (2023). THE ROLE OF ARTIFICIAL INTELLIGENCE IN INCREASING THE DIGITAL LITERACY OF HEALTHCARE WORKERS AND STANDARDIZATION OF HEALTHCARE. no. April, 1-13.

[36] Korovin, Iakov & Kalyaev, Igor. (2015). Modern Decision Support Systems in Oil Industry: Types, Approaches and Applications. 10.2991/tmcm-15.2015.35.

[37] Julka, N. & Srinivasan, Rajagopalan & Karimi, Iftekhar. (2001). A Simulation-based Decision Support System for Refinery Supply Chain Management.

[38] Abdolvahhab Fetanat, Mohsen Tayebi, A picture fuzzy set-based decision support system for treatment technologies prioritization of petroleum refinery effluents: A circular water economy transition towards oil & gas industry, Separation and Purification Technology, Volume 303, 2022, 122220, ISSN 1383-5866, https://doi.org/10.1016/j.seppur.2022.122220.

[39] Cheng, J. C., Chen, W., Chen, K., & Wang, Q. (2020). Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms. Automation in Construction, 112, 103087.

[40] Villamar, D., Soria, R., Rochedo, P., Szklo, A., Imperio, M., Carvajal, P., & Schaeffer, R. (2021). Long-term deep decarbonisation pathways for Ecuador: Insights from an integrated assessment model. Energy Strategy Reviews, 35, 100637.

[41] Quanying Lu, Yuze Li, Jian Chai, Shouyang Wang, Crude oil price analysis and forecasting: A perspective of “new triangle”, Energy Economics, Volume 87, 2020, 104721, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2020.104721.

[42] Pedro L. Castro Verdezoto, Jorge A. Vidoza, Waldyr L.R. Gallo, Analysis and projection of energy consumption in Ecuador: Energy efficiency policies in the transportation sector, Energy Policy, Volume 134, 2019, 110948, ISSN 0301-4215, https://doi.org/10.1016/j.enpol.2019.110948.

[43] Faisal Alqahtani, Nahla Samargandi, Ali M. Kutan, The influence of oil prices on the banking sector in oil-exporting economies: Is there a psychological barrier?, International Review of Financial Analysis, Volume 69,2020, 101470, ISSN 1057-5219, https://doi.org/10.1016/j.irfa.2020.101470.

[44] Saeed Mohammadiun, Guangji Hu, Abdorreza Alavi Gharahbagh, Jianbing Li, Kasun Hewage, Rehan Sadiq, Intelligent computational techniques in marine oil spill management: A critical review, Journal of Hazardous Materials, Volume 419, 2021, 126425, ISSN 0304-3894, https://doi.org/10.1016/j.jhazmat.2021.126425.

[45] Sandra Pérez, Catherine German-Labaume, Sébastien Mathiot, Sylvaine Goix, Philippe Chamaret, Using Bayesian networks for environmental health risk assessment, Environmental Research, Volume 204, Part B, 2022, 112059, ISSN 0013-9351, https://doi.org/10.1016/j.envres.2021.112059.

[46] Jan Roeder, Matthias Palmer, Jan Muntermann, Data-driven decision-making in credit risk management: The information value of analyst reports, Decision Support Systems, Volume 158, 2022, 113770, ISSN 0167-9236.

[47] Hu, W., Almansoori, A., Kannan, P. K., Azarm, S., & Wang, Z. (2012). Corporate dashboards for integrated business and engineering decisions in oil refineries: An agent-based approach. Decision Support Systems, 52(3), 729-741.

[48] Bristone, M., Prasad, R., & Abubakar, A. A. (2020). CPPCNDL: Crude oil price prediction using complex network and deep learning algorithms. Petroleum, 6(4), 353-361.

[49] Tayebi, M., Bemani, A., Fetanat, A., & Fehresti-Sani, M. (2022). A decision support system for sustainability prioritization of air pollution control technologies in energy and carbon management: Oil & gas industry of Iran. Journal of Natural Gas Science and Engineering, 99, 104416.

[50] Meilizar, Luthvina, R., Oktavia, N., & Putranesia. (2023). Decision support system for the feasibility of investment in the virgin coconut oil agro-industry. International Journal of Applied Decision Sciences, 16(1), 42-66.

[51] Tashbulatov, R., Karimov, R., & Valeev, A. (2023, March). Decision Support System for Feasibility Study and Determination the Optimal Way to Increase the Throughput Capacity of Main Oil Pipelines. In 2023 International Russian Smart Industry Conference (SmartIndustryCon) (pp. 269-274). IEEE.

[52] Wahyuddin, S., Rachmat, Z., Abdillah, A., Irfan, A., & Idris, M. (2023). The utilization of drone emprit in seeing the trend of increasing oil fuel through social media data. Journal of Intelligent Decision Support System (IDSS), 6(3), 147-154.

[53] Sarfaraz, A. H., Yazdi, A. K., Hanne, T., Hosseini, R. S., & Moradi, M. R. (2022). A Decision Support System for Evaluating Success Factors of Projects in the Oil and Gas Industry. Mathematical Problems in Engineering, 2022.

[54] Saputra, S. E., Wibisono, A. D., Pratama, R. N. A. C. P., & Amir, F. T. (2023, March). Indonesian Oil and Gas Showroom for Increasing the Oil and Gas Exploration and Production. In Third EAGE Digitalization Conference and Exhibition (Vol. 2023, No. 1, pp. 1-5). European Association of Geoscientists & Engineers.

[55] Cheryauka, A., Safin, D., Vianna, A., Ferreira, E., & Fernandes, W. (2023, September). Generative Modeling and Inverse Mapping for Reservoir Navigation with Shallow-to-Ultra-Deep LWD Electromagnetics. In EAGE Seventh High Performance Computing Workshop (Vol. 2023, No. 1, pp. 1-4). European Association of Geoscientists & Engineers.

[56] Jawad, S., Ledwith, A., & Khan, R. (2022). Project control system (PCS) implementation in engineering and construction projects: an empirical study in Saudi’s petroleum and chemical industry. Engineering, Construction and Architectural Management.

[57] Philip, N. Y., Rodrigues, J. J., Wang, H., Fong, S. J., & Chen, J. (2021). Internet of Things for in-home health monitoring systems: Current advances, challenges and future directions. IEEE Journal on Selected Areas in Communications, 39(2), 300-310.

[58] Lombardo, S., Kinney, J., Blake, D., Chase, S., Stovall, A., Siddiqi, A., ... & de Weck, O. (2023). Accessible satellite data decision support systems for Yurok Tribe forest management. Acta Astronautica.

[59] Antoniadi, A. M., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B. A., & Mooney, C. (2021). Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: a systematic review. Applied Sciences, 11(11), 5088.

[60] Michael, M. (2023). Moisture Optimization and Heating Process Automation of Freeze-Dried Coffee Production: A Case Study at Jacobs Douwe Egberts Peet's (Master's thesis, University of Twente).

[61] Lu, Q., Li, Y., Chai, J., & Wang, S. (2020). Crude oil price analysis and forecasting: A perspective of "new triangle". Energy Economics, 87, 104721.

[62] Fragoso, T. M., Bertoli, W., & Louzada, F. (2018). Bayesian model averaging: A systematic review and conceptual classification. International Statistical Review, 86(1), 1-28.

[63] Nurwahyudin, D. S., Trihastuti, N., & Utama, N. A. (2022). Energy Planning in West Java using Software LEAP (Long-range Energy Alternatives Planning). In E3S Web of Conferences (Vol. 359, p. 01001). EDP Sciences.

[64] Mohammadiun, S., Hu, G., Gharahbagh, A. A., Li, J., Hewage, K., & Sadiq, R. (2021). Intelligent computational techniques in marine oil spill management: A critical review. Journal of Hazardous Materials, 419, 126425.

[65] Schaarschmidt, J., Yuan, J., Strunk, T., Kondov, I., Huber, S. P., Pizzi, G., ... & Wenzel, W. (2022). Workflow engineering in materials design within the battery 2030+ project. Advanced Energy Materials, 12(17), 2102638.

[66] Nguyen, T., Gosine, R. G., & Warrian, P. (2020). A systematic review of big data analytics for oil and gas industry 4.0. IEEE access, 8, 61183-61201.

[67] Opher, T., Duhamel, M., Posen, I. D., Panesar, D. K., Brugmann, R., Roy, A., ... & MacLean, H. L. (2021). Life cycle GHG assessment of a building restoration: Case study of a heritage industrial building in Toronto, Canada. Journal of Cleaner Production, 279, 123819.

[68] Ginart, A., Guan, M., Valiant, G., & Zou, J. Y. (2019). Making ai forget you: Data deletion in machine learning. Advances in neural information processing systems, 32.

[69] Pinheiro Pires, A. P., Martinez-Valencia, L., Tanzil, A. H., Garcia-Perez, M., García-Ojeda, J. C., Bertok, B., ... & Friedler, F. (2021). Synthesis and techno-economic analysis of pyrolysis-oil-based biorefineries using P-graph. Energy & Fuels, 35(16), 13159-13169.

[70] Subahi, A. F. (2023). BERT-Based Approach for Greening Software Requirements Engineering Through Non-Functional Requirements. IEEE Access.

[71] Prati, E., Peruzzini, M., Pellicciari, M., & Raffaeli, R. (2021). How to include User eXperience in the design of Human-Robot Interaction. Robotics and Computer-Integrated Manufacturing, 68, 102072.

[72] Martinez-Rendon, C., Camarmas-Alonso, D., Carretero, J., & Gonzalez-Compean, J. L. (2022). On the continuous contract verification using blockchain and real-time data. Cluster Computing, 1-23.

[73] Garcia Valencia, O. A., Suppadungsuk, S., Thongprayoon, C., Miao, J., Tangpanithandee, S., Craici, I. M., & Cheungpasitporn, W. (2023). Ethical Implications of Chatbot Utilization in Nephrology. Journal of Personalized Medicine, 13(9), 1363.

[74] CHRISTANTO, H. J., SUTRESNO, S. A., DENNY, A., & DEWI, C. (2023). USABILITY ANALYSIS OF HUMAN COMPUTER INTERACTION IN GOOGLE CLASSROOM AND MICROSOFT TEAMS. Journal of Theoretical and Applied Information Technology, 101(16).

[75] Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. IEEE Access, 8, 220121-220139.

[76] Syahputra, Z. (2020). Website Based Sales Information System With The Concept Of Mvc (Model View Controller): Website Based Sales Information System With The Concept Of Mvc (Model View Controller). Jurnal Mantik, 4(2), 1133-1137.

[77] Maratkar, P. S., & Adkar, P. (2021). React JS-An Emerging Frontend JavaScript Library. Iconic Research And Engineering Journals, 4(12), 99-102.

[78] Lock, A. (2023). ASP. NET core in Action. Simon and Schuster.

[79] Campos-Sánchez, F. S., Reinoso-Bellido, R., & Abarca-Álvarez, F. J. (2019). Sustainable environmental strategies for shrinking cities based on processing successful case studies facing decline using a decision-support system. International journal of environmental research and public health, 16(19), 3727.

[80] Mangan, S. D. (2023). A Performance-Based Decision Support Workflow for Retrofitting Residential Buildings. Sustainability, 15(3), 2567.

[81] Tarei, P. K., Thakkar, J. J., & Nag, B. (2021). Development of a decision support system for assessing the supply chain risk mitigation strategies: an application in Indian petroleum supply chain. Journal of manufacturing technology management, 32(2), 506-535.

[82] Pejić Bach, M., Topalović, A., Krstić, Ž., & Ivec, A. (2023). Predictive Maintenance in Industry 4.0 for the SMEs: A Decision Support System Case Study Using Open-Source Software. Designs, 7(4), 98.

[83] Jamali, N., Gharib, M. R., & Koma, B. O. (2023). Neuro-Fuzzy Decision Support System for Optimization of the Indoor Air Quality in Operation Rooms. International Journal of Robotics & Control Systems, 3(1).

[84] Talari, G., Cummins, E., McNamara, C., & O'Brien, J. (2022). State of the art review of Big Data and web-based Decision Support Systems (DSS) for food safety risk assessment with respect to climate change. Trends in Food Science & Technology, 126, 192-204.

[85] Patil, S., & Shankar, H. (2023). Transforming Healthcare: Harnessing the Power of AI in the Modern Era. International Journal of Multidisciplinary Sciences and Arts, 2(1), 60-70.

[86] Mufana, M. W., & Ibrahim, A. (2022). Implementation of smart grid decision support systems. IDOSR Journal of Scientific Research, 7(1), 50-57.

[87] Kayacık, M., Dinçer, H., & Yüksel, S. (2022). Using quantum spherical fuzzy decision support system as a novel sustainability index approach for analyzing industries listed in the stock exchange. Borsa Istanbul Review, 22(6), 1145-1157.

[88] Mangan, S. D. (2023). A Performance-Based Decision Support Workflow for Retrofitting Residential Buildings. Sustainability, 15(3), 2567.

[89] Mwaura, D. W. Exploration and Optimized Siting of Geothermal Wells Using a Web-Based Spatial Decision Support System A Case Study of the Olkaria Geothermal Field.

[90] Pejić Bach, M., Topalović, A., Krstić, Ž., & Ivec, A. (2023). Predictive Maintenance in Industry 4.0 for the SMEs: A Decision Support System Case Study Using Open-Source Software. Designs, 7(4), 98.

[91] Marot, A., Kelly, A., Naglic, M., Barbesant, V., Cremer, J., Stefanov, A., & Viebahn, J. (2022). Perspectives on future power system control centers for energy transition. Journal of Modern Power Systems and Clean Energy, 10(2), 328-344.

[92] Parsamehr, M., Perera, U. S., Dodanwala, T. C., Perera, P., & Ruparathna, R. (2023). A review of construction management challenges and BIM-based solutions: perspectives from the schedule, cost, quality, and safety management. Asian Journal of Civil Engineering, 24(1), 353-389.