Artificial Intelligence for Predictive Analytics in the Petrochemical Industry: A Scoping Review

Sara Mohammadi[1], Sadegh Sulaimany[2*], Aso Mafakheri[2]

***Abstract*— The petrochemical industry, particularly in countries like China, the United States, Saudi Arabia, Russia, Germany, and Iran, plays a significant role in generating value in the petroleum and gas sector. This paper aims to systematically explore the literature to identify key concepts, theories, evidence, and research gaps on the use of artificial intelligence in the petrochemical industry. To achieve this, we conducted a scoping review of eligible English journals and conferences that focus on the computational approach to prediction in petrochemical issues. Our search and investigation, carried out on Google Scholar and Scopus, led to the identification of 34 relevant papers. Our findings, from an application perspective, span categories such as energy saving, leakage, failure and error, chemical and molecular, danger and fire, production processes, price and trade, maintenance, noise, and safety and health. In terms of the computational methods utilized, we identified different versions of neural networks, optimization algorithms, and traditional machine learning algorithms, Markov processes, dimension reduction, network analysis, randomized algorithms, and mathematical modeling. For future work, this paper suggests the exploration of underutilized but promising computational techniques for research problems in the petrochemical industry.**

***Index Terms*— Prediction, Petrochemical, Artificial Intelligence**

I. INTRODUCTION

The petrochemical industry plays a significant role in creating added value in oil and gas resources for many countries. In this industry, by converting the hydrocarbons present in crude oil or gas into new products, a substantial added value is generated for the oil and gas resources of countries. For example, in Iran, petrochemicals have earned the top position in non-oil exports, contributing significantly to sustainable development and economic prosperity [1]. Although in terms of production volume, petrochemicals account for approximately 10% of the entire oil industry worldwide, they allocate a much larger share of the total industry value [2]. Petrochemicals have become global since the 1960s, with a remarkable increase in investments. Its global trade has shown more significant growth compared to other products. For instance, the global production of plastics, a major petrochemical-based product, has grown tenfold since 1970, surpassing other raw materials such as metals and cement [3].

In pursuit of conducting impactful applied research in the industry and society, a global focus can be directed towards research related to petrochemicals. One area of interest for domestic policymakers is gaining insights into various predictive aspects of petrochemicals from a computational perspective. These predictions can relate to areas such as trade, maintenance, leakage, processes, and more, each holding its own appeal for domestic industries. Furthermore, gaining a proper understanding of computational prediction methods in the petrochemical industry can open up new or related scientific fields for researchers in the domain of artificial intelligence and petrochemicals. On the other hand, artificial intelligence, as a rapidly growing scientific field, has demonstrated its applications across various domains. The methods employed in artificial intelligence can be utilized for data analysis, pattern recognition, the discovery of new relationships, as well as reasoning and identifying cause-and-effect relationships, especially when applied in the industrial context [4]. The variety of artificial intelligence methods and approaches for tackling various challenges within the petrochemical field can present decision-making complexities for researchers in this realm. This becomes particularly pertinent when there isn't a prevailing or specialized method to apply in a specific area or when there is a need to compare and assess different methodologies. Having a comprehensive understanding and perspective can be beneficial.

Our goal in this paper is to thoroughly examine every computational prediction technique applied in the petrochemical sector from every angle. This study serves as a scoping evaluation of all English-language articles published in respectable journals and conferences. It offers a variety of perspectives on the uses of artificial intelligence techniques in the petrochemical sector. For that reason, the following primary goals are pursued by this study:

1. What are the computational prediction methods used in petrochemicals?
2. What are the operational domains within the petrochemical industry where computational prediction has been applied?
3. Identifying and analyzing various areas with the potential for scientific and practical activities related to prediction in petrochemicals.

The rest of this paper is organized as follows. In Section 2, the method of literature review and gathering relevant sources will be elucidated. Then, in Section 3, the findings, interpretations, and relevant insights will be presented in diverse charts. Finally, in Section 4, a summary, along with the potential and future research directions, will be discussed.

1: Department of Economics, Razi University, Kermanshah, Iran
2. SBNA Lab, Department of Computer Engineering, University of Kurdistan, Sananadaj, Iran
Corresponding author: s.sulaimany@uok.ac.ir

II. METHOD

This study is based on a scoping review of papers related to prediction in the petrochemical industry. Indeed, scoping review is a type of research synthesis that seeks to "map the literature on a particular topic or research area and provide an opportunity to identify key concepts, gaps in the research, and types and sources of evidence to inform practice, policymaking, and research" [5]. According to [6], a scoping study is undertaken for the following objectives:

1. To examine the extent, range and nature of research activity
2. To determine the value of undertaking a full systematic review
3. To summarize and disseminate research findings
4. To identify research gaps in the existing literature

On the other hand, as a special type of systematic review, scoping review seeks to provide a comprehensive, unbiased synthesis of many relevant studies in a single document for a topic that has the potential to grow [7]. In simpler terms, a scoping review seeks to present a summary of different research papers about a wide subject, while a systematic review seeks to gather scientific evidence from a smaller group of studies about a specific research question [8].

In the process of this scoping review, two prominent databases, Google Scholar and Scopus, were utilized, offering substantial coverage of the research field. Google Scholar is capable of searching only within full texts (if available) or article titles, whereas Scopus provides the capability of separate keyword searches. The research timeframe considered in this study ranges from the year 2000 onwards. The selected articles were sourced from journals and conferences, with books and theses excluded. The standard and commonly used protocol for visualizing the systematic review process is the PRISMA diagram [9]. In this study, we employ the PRISMA diagram, as illustrated in Fig. 1, to delineate the details of the scoping review process. In the process of collecting relevant references, duplicate articles, non-English language articles, and articles with unrelated content were excluded. Ultimately, 34 valid studies were identified and examined.

III. RESULT AND DISCUSSION

The number of conference papers compared to journal papers was 6 to 29 (see Fig. 2, right side). Among them, the "energy" journal had the highest number of published papers. The count of research papers published by mid-2022 shows a gradual increase, as illustrated in Fig. 2 (left side). Additionally, more than one-fourth of the papers have been published directly in journals.

An examination of the papers concerning their practical applications in the petrochemical industry reveals at least 11 distinct prediction areas, as stated in Table I. Fig. 3 depicts the contribution of each of these applications. It is evident that a significant focus in petrochemical prediction research has been on maintenance. This could involve predicting equipment failures, optimizing maintenance schedules, and so on.

The Energy Savings category in the pie chart represents 15% of the computational prediction research in the petrochemical industry. This suggests that a significant portion of the research is focused on improving energy efficiency and reducing energy consumption in the industry.

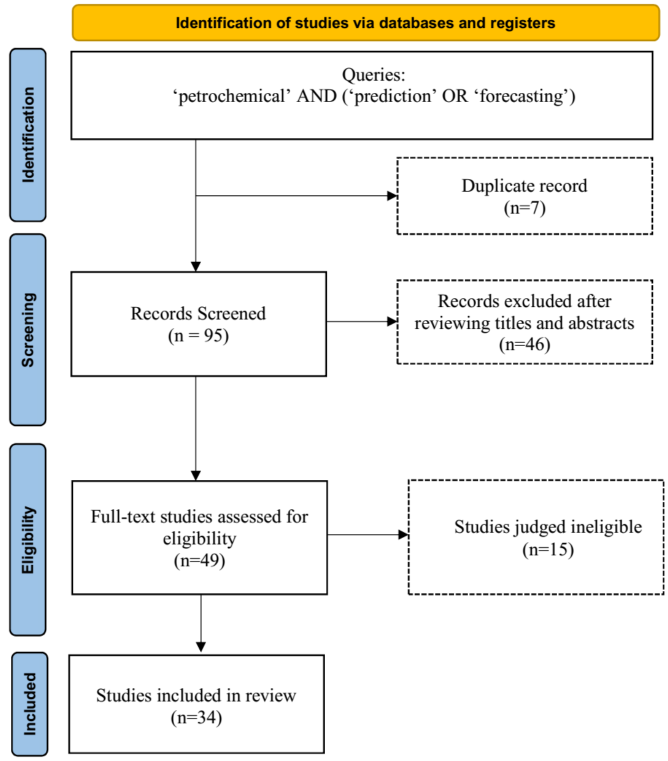

Fig. 1. The process of collecting relevant references for a scoping review, as depicted in the PRISMA diagram

Energy-saving tactics in the petrochemical sector can take many different forms, including waste reduction, equipment efficiency improvements, and manufacturing process optimization. These tactics may heavily rely on computational prediction techniques. For instance, using past data, machine learning algorithms may be used to forecast energy use and find areas where energy savings might be made.

However, it's important to note that while 15% is a significant portion, there is still a lot of potential for further research in this area. Energy efficiency is a critical issue for the petrochemical industry, given the industry's substantial energy use and the global need to reduce greenhouse gas emissions. Therefore, this is an area where further application of computational prediction methods could have a significant impact.

The Trade and Pricing category in the pie chart represents 13% of the computational prediction research in the petrochemical industry. This suggests that a significant portion of the research is focused on predicting trade patterns and pricing trends in the industry.

Trade and pricing in the petrochemical industry can be influenced by a wide range of factors, including supply and demand dynamics, geopolitical events, regulatory changes, and technological advancements. Computational prediction methods can be used to analyze these factors and predict future trade and pricing trends [10]. For example, machine learning algorithms can be used to analyze historical trade and pricing data, identify patterns, and make predictions about future trends. These predictions can help industry stakeholders make informed decisions about production, investment, and marketing strategies.

With a slight margin, predictions related to pipe and equipment leakage, faults and failures, and hazards and fire incidents are among the significant areas of interest in relevant scientific research. The total number of studies seems to be around 40, as some papers have focused on more than one prediction domain.

A substantial focus of the algorithms and methods used for prediction has been the utilization of large datasets for application in neural networks and deep learning. It is evident that when prediction accuracy surpasses the intricacies of process formation, the utilization of black-box methods for algorithm learning and generating more accurate outputs from training data becomes more favored. Consequently, in the classification of computational methods employed, neural network-based methods are distinguished from other common machine learning methods such as regression. Additionally, due to specific applications like dimensionality reduction or optimization algorithms, these aspects are also considered separately. Notably, promising areas such as a network-based perspective on petrochemical-related data have not been extensively explored. Especially in the realm of business communications, complex network theories can be harnessed to create greater added value and unearth previously overlooked patterns. Some methods that are based on software development or the use of previous statistical data have been categorized as "other." It's worth noting that the total number of methods does not align with the total number of papers because in some papers, two or more computational methods were used simultaneously for prediction.

TABLE I
Petrochemical Prediction Areas

Area	Papers
Energy savings	[14], [15], [16], [17], [18] [10]–[14]
Leakage-related issues	[19], [20], [21]
Faults and failures	[22], [23], [24]
Chemical and molecular aspects	[25], [26]
Hazards and fire incidents	[27], [28], [29]
Production and related processes	[30], [31], [32], [33], [34]
Trade and pricing	[10], [35], [36], [37], [38], [39], [40]
Product properties	[41]
Equipment maintenance	[42], [43], [44], [45], [46]
Noise	[47]
Safety and health	[48]

The quantity of papers associated with each computational method is depicted in Fig. 4 as a treemap. A particular computational technique and a number denoting the number of studies linked to it are labeled for each area of the treemap.
The neural network is the most researched method, with 15 studies. Neural networks are a set of algorithms modeled loosely based on the human brain, designed to recognize patterns. They interpret sensory data through a kind of machine perception, labeling or clustering raw input. Probably it is due to their ability to recognize complex patterns and correlations in raw data, much like the human brain. They are capable of interpreting sensory data through a kind of machine perception, labeling or clustering raw input, and continuously learning and improving over time. This makes them highly effective in handling complex and non-linear relationships within data, which is particularly useful in industries like petrochemicals where the relationships between variables can be complex and non-linear.

In addition to this, neural networks are capable of handling large datasets and finding predictive patterns within them. This is beneficial in industries like petrochemicals that generate large amounts of data. With the advent of deep learning, which is essentially neural networks with many layers, predictive analytics has taken on a whole new level of sophistication. Furthermore, neural networks are versatile and find applications in various predictive analytics tasks, including image recognition, natural language processing, and time series forecasting. Their ability to continuously learn and improve makes them ideal for predictive analytics, where the goal is to improve the accuracy of predictions over time.

Each of the optimization algorithms, traditional ML (machine learning), and mathematical modeling methods has been the subject of 2 researches projects. Optimization algorithms are used to adjust the parameters of a model to improve its performance. Traditional ML refers to more established machine learning methods like decision trees, linear regression, etc. Mathematical modeling involves the use of mathematical structures to represent real-world situations.

Also, dimensionality reduction, Markov process, random algorithms, and network analysis, which has only one associated study, are important computational methods with several potentials for future use. Dimensionality reduction is the process of reducing the number of random variables under consideration by obtaining a set of principal variables. A Markov process is a stochastic process that satisfies the Markov property. Random algorithms are algorithms that make random choices as part of their logic. Network analysis involves the study of complex systems as a network of interconnected elements.

Eventually, the application of artificial intelligence in the petrochemical industry presents several challenges and opportunities. Here are some of the key challenges and potential solutions, citing recent related papers:

A. Challenges

1. Data Management: The petrochemical industry generates a vast amount of data. Managing this data effectively for AI applications can be challenging [11].

2. Predicting Equipment Failure: One of the main challenges in the oil refining and petrochemical industries is to continue operating while maintaining production equipment [12].
3. Operational Costs: The oil and gas sector is facing the challenge of significantly decreasing operating costs without compromising safety [11].
4. Adoption of AI: Technical and non-technical factors affecting the adoption of machine learning technologies can be a challenge [13].

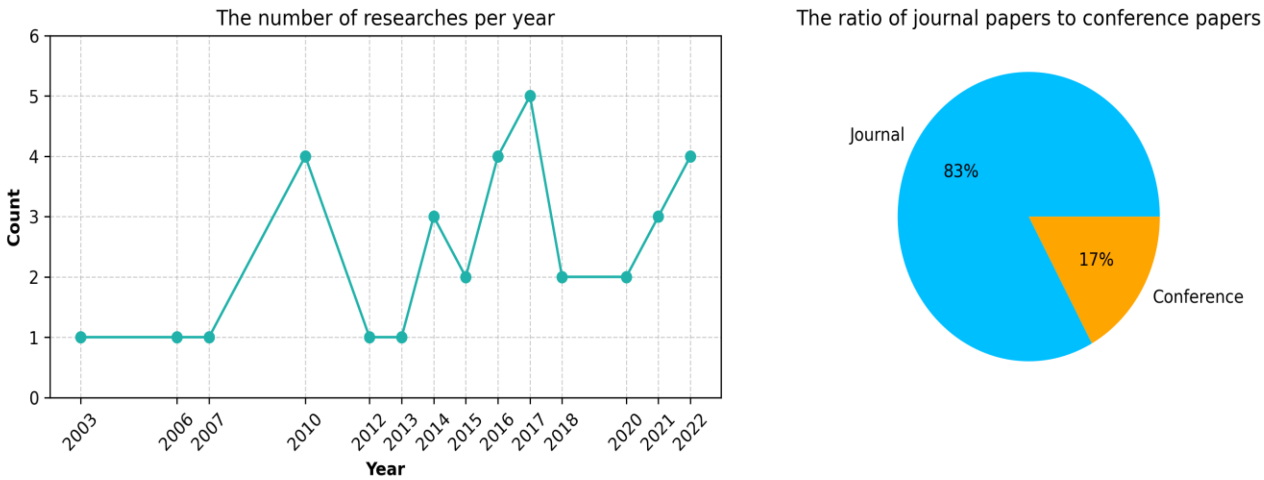

Fig. 2. The right side shows the ratio of journal papers to conference papers and the left side shows the number of published papers per year

B. Solutions

1. Improved Data Management: Technological improvements and the big data revolution can help provide the information needed for decisions to be made and reduce the time from identification to execution [11].
2. Predictive Maintenance: AI and machine learning can be used to predict equipment failure, thus preventing costly shutdowns [12].
3. Cost Reduction: AI has been engaged widely to resolve challenges in the oil and gas industry, including operational cost reduction [11].
4. Promoting AI Adoption: Evaluating and addressing the technical and non-technical factors affecting the adoption of machine learning technologies can help promote the use of AI in the industry [13].

It’s also worth noting that the petrochemical industry is a rapidly evolving field, and new challenges and solutions are likely to emerge as technology advances and the industry’s needs change. Therefore, continuous research and staying updated with recent literature are crucial.

IV. CONCLUSION AND FUTURE WORKS

Despite the global significance of investment in oil and raw materials needed for energy supply, there has been a notable focus in recent decades on value-added derivatives such as petrochemicals. Various research efforts have also been undertaken to provide practical insights into this industry. Part of these research endeavors has been directed towards predicting various aspects, which holds significant importance, especially for policymakers in Iran as one of the world's petrochemical exporters. One of the objectives of this research was to gain insight into the techniques employed and the areas investigated for prediction in the petrochemical industry. This insight was achieved through a scoping review in collaboration with experts in the fields of economics and computer science. Following this research, it is possible to conduct studies related to the petrochemical industry that do not have domestic or Persian examples to generalize and apply them to the domestic industry. Furthermore, as this paper only focuses on English journals and papers, conducting similar domestic research can enable a comparative analysis and facilitate the provision of precise findings. It is worth considering the limitations of artificial intelligence for prediction in petrochemical. While artificial intelligence is capable of modeling complex, nonlinear relationships, which makes them suitable for many prediction tasks in the petrochemical industry, it often requires large amounts of data for training, and it can be prone to overfitting if not properly regularized [14].

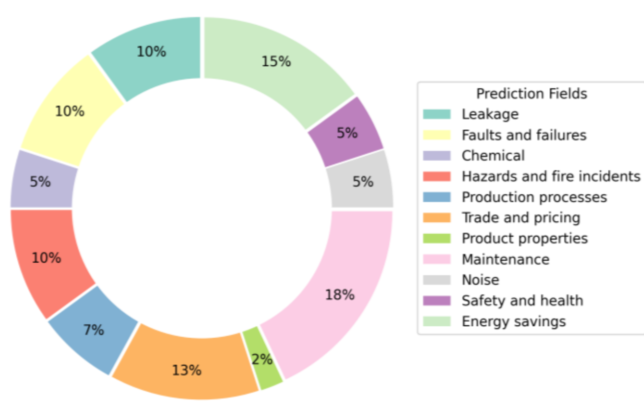

Fig. 3. Various fields within the petrochemical industry where computational prediction research has been published as valid scientific research

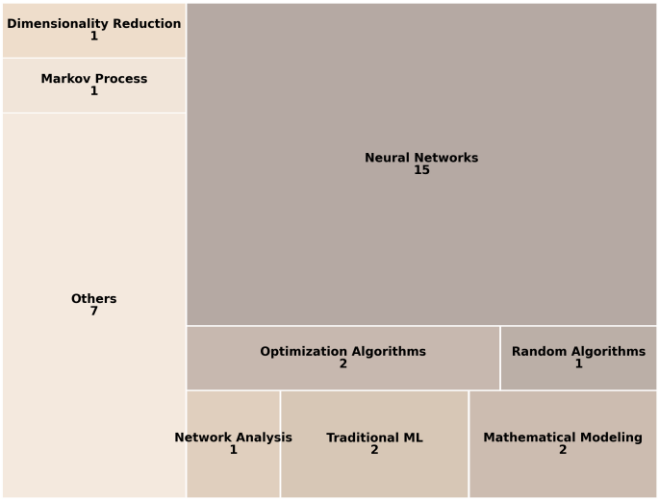

Fig. 4. Various computational methods commonly used for prediction in the petrochemical industry, primarily within the field of artificial intelligence

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