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Review Article

Process Integration in Optimising the Oil and Gas Supply Chain

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ABSTRACT

The oil and gas supply chain encompasses multiple links, and its optimisation is transforming into intelligent, sustainable development. Considerable research has been conducted to reduce carbon emissions and environmental effects while reducing operational costs and promoting green supply chain management. This paper details process-integration methods (e.g. Pinch Analysis and mathematical programming methods), introduces and summarises common tools, analyses problem considerations, constructs models and solution algorithms, and summarises the results in similar fields. The study found that the optimisation of this supply chain should consider multiple objectives, including economics, environmental effects and social aspects and emphasise the importance of supply and demand balance, cost optimisation and sustainability. Future research should develop efficient algorithms to solve complex optimisation problems and incorporate big data and real-time monitoring technology to enhance system resilience and adaptability. Synergistic interdisciplinary research promotes new methods and technology for sustainable development in the oil and gas industry.

KEYWORDS

Process Integration, Optimisation, Supply chain, Mathematical programming, Low-carbon emissions, Sustainable utilisation.

INTRODUCTION

In 2023, oil consumption in China reached 756 million tonnes, with refined oil consumption at 399 Mt and natural gas consumption at 391.7 Gm^3 [1]. A robust consumption market requires a reliable logistical system to meet the substantial oil and gas transportation demands. In China, the annual volume of gas entering the primary transmission network of China's natural gas pipeline system exceeds 220 Gm^3 [2]. Efficient oil and gas logistics optimisation can enhance the overall operational efficiency of the supply chain. Meeting user demands while reducing logistics costs significantly decreases carbon emissions associated with transportation. This approach is crucial for improving economic efficiency and sustainable development [3].

Against the growing global energy demand, the oil and gas industry is facing unprecedented challenges as a critical source of energy supply. According to the International Energy Agency,

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global demand for oil and gas is expected to grow continuously over the next few decades, placing greater demands on the flexibility and efficiency of the oil and gas supply chain. However, the current oil and gas supply chain faces problems, such as excessive costs, inefficiencies and environmental effects. Oil and gas supply chain optimisation is a complex problem where decision variables (e.g. transportation route selection [4], distribution schemes, and loading plans) can significantly affect transportation costs [5]. The types of transportation equipment, nature of the transport medium, fuel prices, access time limitations at stations and ports, and loading capacity restrictions further increase the complexity of the problem [6]. The oil and gas transportation process involves multiple stages, such as upstream exploration [7], midstream transportation [8], and downstream marketing [9]. Considering the potential for optimisation in the oil and gas supply chain at global, national, regional and local levels, many studies have researched this problem [10].

Researchers have focused on improving the efficiency of oil and gas supply chains by improving innovation and management [11]. For example, big data analysis and machine learning can optimise demand forecasting and resource allocation by integrating modern digital technology into oil and gas transportation and capabilities [12], which can improve their competitive advantage and innovate performance and processes [13]. In addition, by constructing mathematical models, researchers are able to clearly describe and quantify the relationships among various components, particularly under different constraints. These models have been widely applied in multiple fields, such as demand forecasting [14], inventory management [15], and transportation scheduling [16]. They provide decision-makers with a scientific basis, enabling them to make optimal decisions under complex constraints [17]. Simulation techniques evaluate the risk due to uncertainty [18], and the dynamic behaviour of each link in the supply chain is simulated to assess the system performance [19]. The relationship between process characteristics and economic growth is analysed through the framework of graphical modelling [20]. Although various approaches to studying supply chain optimisation have been taken, this paper reviews the current problems in optimising the oil and gas supply chain from the perspective of process integration, exploring how to integrate the links and their intrinsic relationships systematically and achieve synergistic efficiencies and deficiencies at the design and operation levels.

Process integration is a broad concept, a set of methods combining several parts or the whole process to view problems from a more integrated perspective to reduce resource consumption and emissions, such as greenhouse gases (GHGs) [21]. Process integration initially focused on heat integration and has evolved into the Pinch Analysis, which remains a widely employed heat integration method [22]. At its core, it represents a holistic approach to process design and operation, emphasising the mutual utilisation of materials and energy in multiple processes [23]. Specific processes require external heat input to address the heat integration problem, whereas others necessitate cooling. The application of temperature matching to optimise heat exchange between these two processes enables the efficient recovery and use of generated waste heat. This approach can significantly reduce the demand for external utilities and achieve the desired temperature adjustments in the processes [24].

The principles of process integration have been applied to quality networks, such as water networks [25]. These approaches enhance water resource efficiency and reduce the consumption of clean water by optimising the allocation, utilisation[26], and regeneration of various grades of water resources in chemical parks [27]. The supply chain also presents similar opportunities for integration [28]. Adopting a holistic approach to resource allocation can achieve an optimal match between supply and demand [29]. This strategy enhances the efficiency of the supply chain and reduces energy consumption, costs [30], and environmental pollution associated with its operations [31]. Therefore, optimising the oil and gas supply chain from the process system integration perspective involves optimising individual components or subprocesses and emphasising the global optimality of the entire supply chain system. This approach integrates existing resources, minimises waste at individual stages, and optimises the cost structure, maximising overall efficiency and effectiveness.

This paper describes the existing process-integration methods, including Pinch Analysis, mathematical programming methods, and P-graph methods (Figure 1). In addition, it introduces and summarises commonly used tools, provides a new perspective on optimising oil and gas supply chains, and emphasises the necessity of systemic wholeness, economy, sustainability and technical efficiency improvement. Compared with the traditional literature, this paper summarises the existing optimisation techniques and explores how to achieve systematic and sustainable optimisation by integrating different methods and technology. This study presents directions for future research, providing new ideas and case studies to support industry practices and promote the oil and gas industry's move toward a more efficient, transparent and sustainable direction.

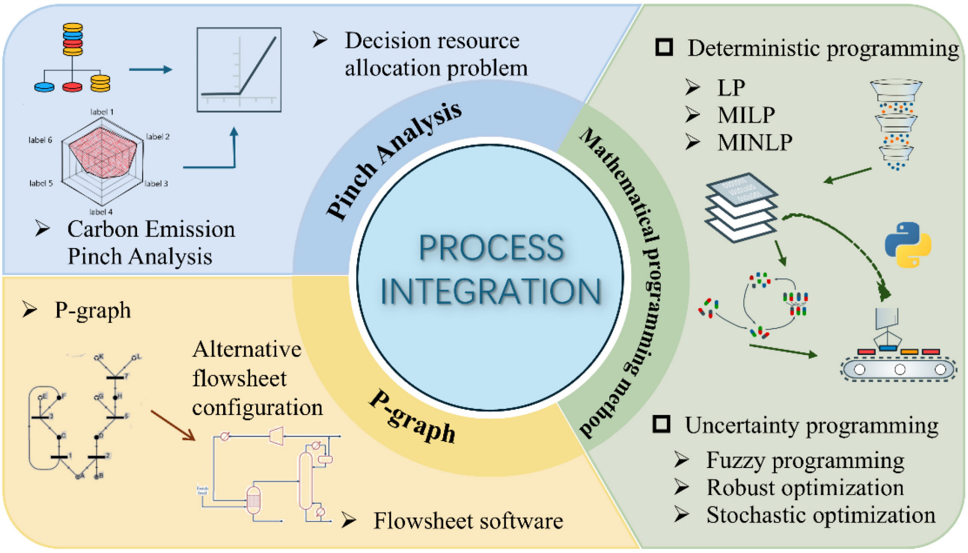

Figure 1. Literature review diagram

METHODS

This paper summarises a series of advanced optimisation methods from the process-integration perspective to deal effectively with the current challenges facing the energy supply chain. These methods focus on improving the efficiency of individual links and emphasise the overall optimisation of the entire supply chain system. The study aims to balance economic benefits and environmental effects to ensure sustainable development with limited resources by introducing multi-objective programming and uncertainty analysis.

Pinch Analysis

The Pinch Analysis has been applied to supply chain problems and studied in supply chain optimisation, performance assessment, and environmental impact assessment [32]. The Pinch Analysis was initially derived from the thermodynamic problem of combining and matching logistics requiring heating or cooling in a chemical process to improve energy efficiency. In heat integration problems, many industrial processes require an external heat source, whereas some processes also require cooling. The potential for heat exchange between these processes can be identified through a Pinch Analysis [33].

Scholars use a similar concept in supply chain optimisation problems, often drawing separate combinatorial curves for supply and demand. These curves are matched to visualise the inventory situation at the beginning and end of a period and determine whether shortages or overages occur at various time points. This method helps decision-makers visualise the inventory situation and energy requirements at different times. This visualisation allows users to identify potential shortages or surpluses quickly so that they can adjust accordingly [34].

The earliest application of the Pinch Analysis to a supply chain problem was in 2002 [35], which introduced the idea of the pinch point method in supply chain planning by proposing a combinatorial graph for a supply chain problem using the number of products as the horizontal axis and time as the vertical axis (Figure 2). Given the demand, the minimum productivity is calculated, and the resulting logistics planning scheme reveals the surplus and shortage of inventory as it fluctuates over time, where the pinch point is the time at which zero inventory occurs. This method enables a quick observation of how production, capacity, distribution and inventory can be adjusted to maximise profits while meeting specific period and demand targets.

A follow-up study by Singhvi et al. [36] applied the proposed Pinch Analysis to two arithmetic cases and compared the results with those of the equivalent problem solved using GAMS. The initial solution provided by the pinch point method effectively saves the time required to solve the GAMS model, which is one-sixth of the time required to solve the model directly. Moreover, in[37], the extended prioritised cost was proposed, and Pinch Analysis was applied to determine the cost minimisation scheme in the resource allocation problem. The internal resource invocation and inter-regional resource scheduling methods in the studied region were determined by rationalising the planning of dedicated and general-purpose resources.

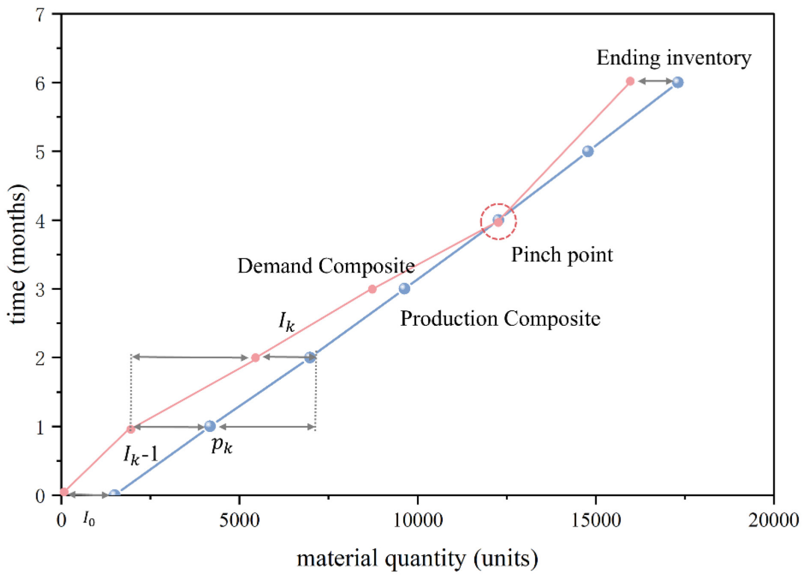

Figure 2. Typical composites by Pinch Analysis (adapted from [35])

The carbon Pinch Analysis is also an effective method for supply chain planning (Figure 3) [38]. The method provides a convenient graphical tool. The aim is to meet the energy needs of the study area, and this method can visualise how the adjustment of the energy mix can reduce carbon emissions to enable the study area to meet the planned carbon emission targets. Li et al.[39] used the Pinch Analysis to plan regional electricity and biomass energy supply chains under carbon emission constraints. The biomass supply from various regions was adjusted and plotted in the electricity demand and carbon emission maps to determine the required minimum external electricity supply. Hwangbo et al.[40] proposed a hybrid carbon dioxide (CO_2)-hydrogen Pinch Analysis for hydrogen energy supply chains to compare the differences in environmental costs visually between existing and integrated supply chains. Figure 4 illustrates the kilograms of CO_2 equivalent for H_2 demand in various processes.

Moreover, in [41], a Pinch Analysis was employed for bioenergy supply chains to compare the GHG emissions of different energy supply GHG emissions of various energy supply options.

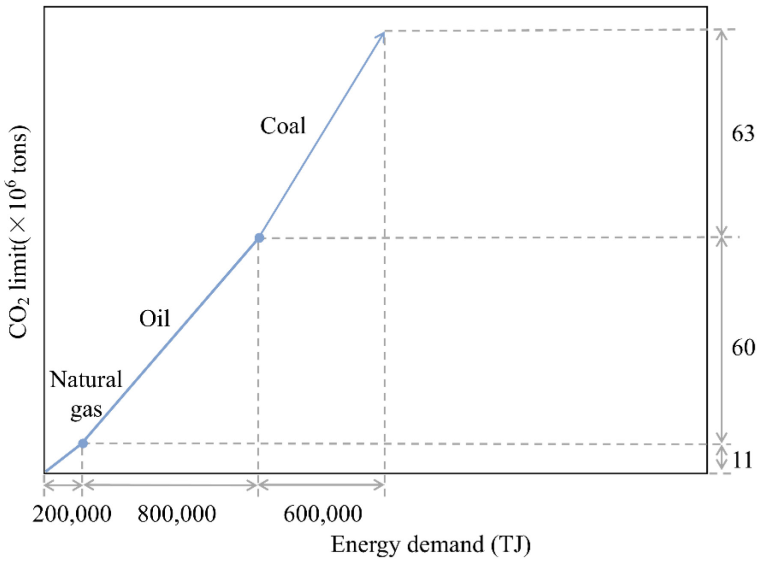

Figure 3. Comparative analysis of greenhouse gas emissions by energy demand (adapted from [38])

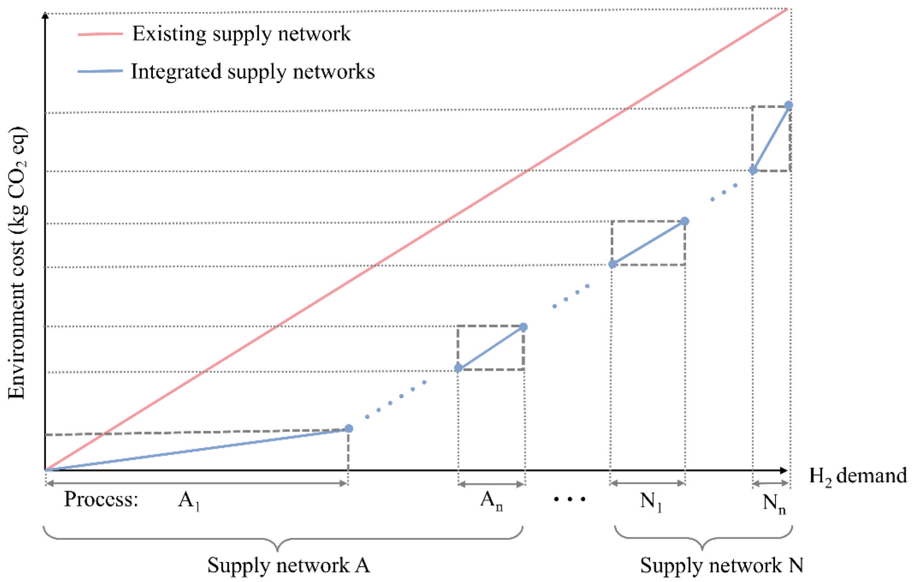

Figure 4. Mixed carbon dioxide-hydrogen energy Pinch Analysis (adapted from [40])

With the development of the Pinch Analysis, its application has expanded to uncertain optimisation and multi-objective optimisation. These extensions enable Pinch Analysis to provide higher-quality initial solutions and accelerate the mathematical programming solution process when facing complex supply chain problems. For example, Priya and Bandyopadhyay [42] proposed a multi-objective Pinch Analysis method, which weighs the cost and quality of various resources.

In addition, the Pinch Analysis considering uncertainty has been assessed; for example, Bandyopadhyay [43] investigated how to synthesise the source-sink network without accurate parameters. The proposed method expresses uncertainty as intervals, sets upper and lower bounds on parameters, and explores the solution process of the resource planning problem.

Jalanko and Mahalec [44] applied a supply-demand pinch-based algorithm to optimise gasoline blending for multiperiod planning under component quality uncertainty. They examined its performance on a full space model. These extensions enable Pinch Analysis to provide higher quality initial solutions and accelerate the subsequent mathematical programming solution process when facing complex supply chain problems.

Visualisation is the most significant advantage of the Pinch Analysis based on this overview and analysis. The Pinch Analysis can reduce energy consumption and costs and improve the overall efficiency of the supply chain via effective heat integration and resource allocation. In supply chain planning problems, users can obtain a preliminary supply and demand planning scheme for the supply chain using simple calculations.

In addition, the difference in results from various scenarios can be visualised by panning the supply curves. The method can also provide a high-quality initial solution, accelerating the solution speed using mathematical planning methods to determine a better solution. The development of the Pinch Analysis continues to evolve into a broader range of application scenarios, such as uncertain and multi-objective optimisation, but further research is still necessary to improve the applicability and reliability of the method.

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Mathematical programming method

The complex, dynamic oil and gas storage and transportation logistics supply chain involves all aspects, from raw material collection, transportation and storage to the final product delivery (Figure 5). Optimising the efficiency and cost of this supply chain has become critical as global energy demand increases and market competition intensifies. In the oil and gas storage and transportation logistics supply chain, mathematical programming has been used as an effective tool to optimise aspects of resource allocation, reduce costs, improve efficiency and meet market demands. Common models include linear programming, mixed integer linear programming (MILP), and mixed integer nonlinear programming (MINLP), where objective functions and constraints are set to realise the ideal state.

Mathematical programming methods enable determining the optimal supply chain network structure. Moreover, these methods can optimise inventory levels in uncertain market environments and transportation routing and scheduling. It employs an objective function to minimise transportation or total inventory costs to meet market demand and flow balances, forecast demand based on different time frames, adjust the inventory strategy and determine the optimal transportation solution.

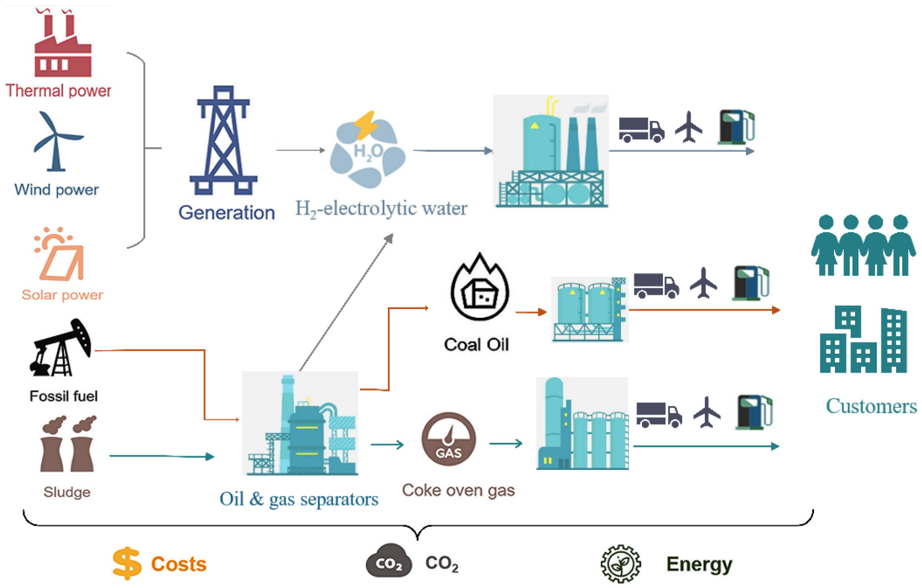


Figure 5.Oil, gas, and hydrogen supply chain

Deterministic programming. In deterministic programming, all parameters are known and deterministic, meaning no uncertainty or randomness exists in the model. This approach is suitable for scenarios where future conditions can be accurately predicted and based on which optimisation strategies can be developed to improve operational efficiency and reduce costs.

Deterministic planning has a wide range of applications in the petroleum supply chain, covering the entire process, from crude oil extraction to refined product distribution (e.g. facility siting, capacity programming and profit maximisation). Bandyopadhyay et al. [45] proposed a deterministic model for the strategic design and programming of refined oil product supply chains that make decisions regarding optimal depot locations, storage capacities, transportation modes and routes for the long term. Kazemi and Szmerekovsky [46] proposed a MILP model to determine the optimal location for a product distribution centre for refined petroleum, storage capacity, transportation mode and transhipment volume. In [15], a multi-objective supply chain optimisation model for refined petroleum products was proposed, considering the three objectives: minimising costs, maximising profits and maximising service levels.

English literature is currently characterised by greater versatility of the established model, better fit to the situation, and more considerations than domestic literature. In addition, the deterministic model is primarily applied to formulate distribution plans for a specific period under known production, demand and transportation infrastructure conditions. However, due to its inability to account for uncertain factors, such as fluctuations in production and demand, this model is unsuitable for long-term logistics planning. Therefore, the derived logistics planning scheme may struggle to meet distribution requirements during peak periods of oil production demand.

Mathematical programming has also been studied in many models for optimising the hydrogen supply chain. For example, Montignac et al. [47] developed and implemented a multi-objective dynamic optimisation model based on the MILP model to analyse the trade-off between cost and carbon emissions in the hydrogen supply chain. Dautel et al. [48] developed an industrial decarbonisation MILP model that considers the local grid and renewable power supply, hydrogen production, compression, and storage and transport to the user. The method obtains the minimum cost by optimising the hydrogen supply chain when demand is known. Zhou et al. [49] proposed a novel multi-objective optimisation model for a multiperiod urban hydrogen supply chain, finding that multi-objective optimisation is more effective than single-objective optimisation when focusing on only the minimum cost and maximum hydrogen demand coverage. The study results revealed that multi-objective optimisation better balances conflicting objectives. Li et al. [50] developed a MILP model for the hydrogen supply chain design considering the primary energy availability, production technology options, transportation modes and storage types in Dalian, China. Further, De-León Almaraz et al. [51] proposed a multi-objective MILP model to achieve the averaged cost, potential risk of global warming, and social cost-effectiveness of the hydrogen supply chain, considering economic, environmental and social aspects.

Mathematical models for optimising the CO_2 supply chain often involve multiple links, including CO_2 capture, transportation, storage and utilisation. D'Amore and Bezzo [52] introduced a MILP framework for the strategic design and programming of a large-scale European supply chain for carbon geo sequestration, where the entire network was economically optimised over a 20-year time horizon to provide the geographic location and size of the capture and storage sites and the most convenient transportation modes and routes.

Moreover, Akgul et al. [53] proposed a multi-objective MINLP model to optimise a biomass-based supply chain, including carbon capture and storage for the UK. Kalyanarengan Ravi et al. [54] employed a MILP model to select suitable sources, capture technology transportation networks and CO_2 storage sites and optimise the lowest total cost of CO_2 emission reductions across the Netherlands. Wu et al. [55] proposed an optimisation model to support regional carbon capture, transport, and sequestration programming under uncertainty with a least-cost strategy supporting CO_2 capture and sequestration programming in a localised region.

To improve the profitability of the natural gas supply chain, Arya et al. [56] compared the effects of the genetic algorithm, generalised reduced gradient, and ant colony optimisation (ACO) algorithms with the objective of the value of fuel consumption using the natural gas supply chain of France as an example. They concluded that ACO is the most efficient algorithm in searching for an approximate globally optimal solution. Liu et al. [57] introduced new energy sources to reduce the energy consumption of the compressor and established a low-carbon and low-energy operation model. They employed an improved particle swarm optimisation (NHPSO-JTVAC) algorithm to solve the model. **Figure 6** presents the optimisation objective iteration process. In addition, Wei et al. [58] developed a stochastic optimisation algorithm that integrates particle swarm optimisation and high-fidelity simulation for solving a complex MINLP model to maximise energy consumption reduction during pipeline operation. Rodríguez et al. [59] applied a meta-heuristic algorithm of simulated annealing for optimisation to determine the optimal pipeline layout and location of the installation nodes.

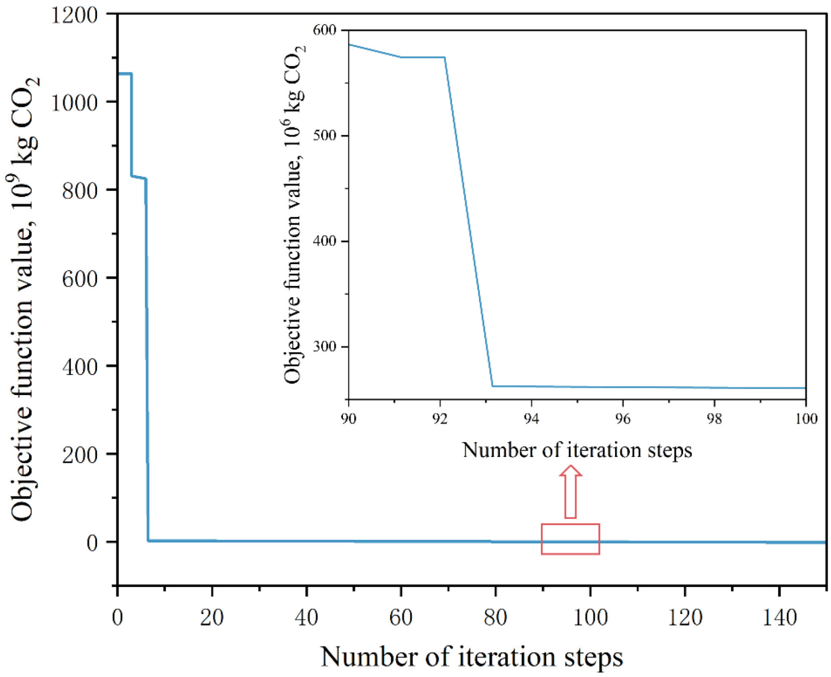


Figure 6. Steps to determine the optimal solution iteratively (adapted from [57])

Moreover, Arya and Honwad [60] developed a steady-state model combining the properties of gas hydrodynamics, compressor characteristics, and other factors to minimise fuel consumption in the pipeline network using an ACO algorithm to achieve a fixed throughput. Mikolajková et al. [61] employed the segmental linearisation of the MINLP model into a MILP to solve the optimal operation of the natural gas distribution problem, considering technical and operational aspects. Wang et al. [62] proposed a MILP model based on the topology of the existing natural gas pipeline, load and pressure at each node to modify natural gas pipelines, inject hydrogen into the pipeline, and minimise the pipeline replacement and compressor operation costs. Zhou et al. [63] established an automated corresponding framework for optimising the operation of large, complex natural gas pipelines with coupled data and mechanisms, in which the optimisation modelling of the MILNP model was applied to reduce the energy consumption to determine the most economical operation scheme.

Deterministic programming has played a critical role as an optimisation tool in supply chain management, especially in refined oil products, hydrogen and natural gas, demonstrating its broad application potential. **Figure 7** summarises the commonly employed algorithms and models. However, although deterministic programming can provide clear solutions in many cases, its limitations should not be ignored. With the development of data science and artificial intelligence technology, combined methods (e.g. uncertainty programming, dynamic programming and multi-objective optimisation) may become a new trend in research.

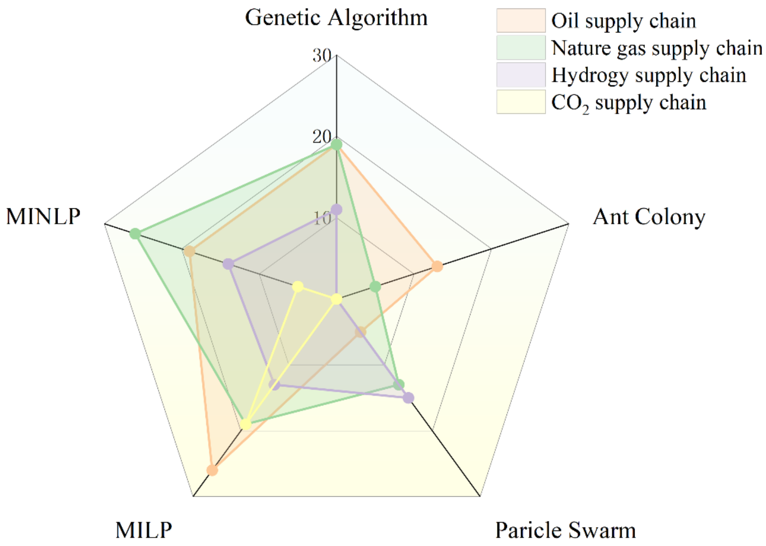


Figure 7. Commonly used models and algorithms

Uncertainty programming. Uncertainty programming offers an effective optimisation tool for oil and gas supply chain management, helping decision-makers make better decisions in complex and uncertain environments. Through rational modelling and solving, uncertainty programming can improve the flexibility, responsiveness and overall efficiency of the supply chain. In the practical application of oil and gas supply chains, demand, supply and price are often stochastic, as illustrated in **Figure 8**, and uncertainty studies provide an effective framework to optimise the decision-making and maximise the expected benefits or minimise the risks.

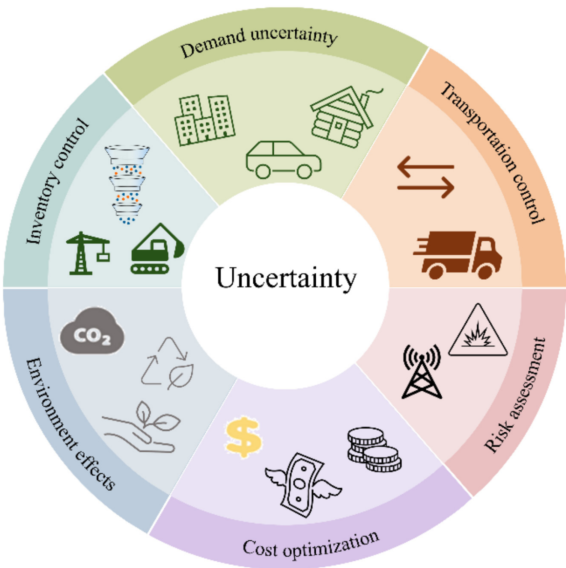
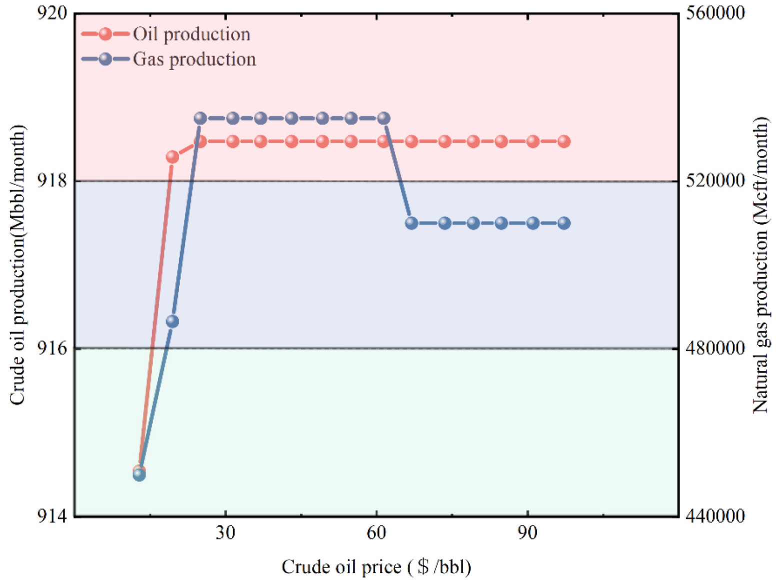


Figure 8. Uncertainty sources

Many studies have analysed the effectiveness of various uncertainty models in oil and gas supply chains via empirical cases, especially the downstream uncertainty in the supply chain, which has been studied in depth. Alnaqbi et al. [64] proposed a multiproduct, multicycle stochastic programming model considering cost and demand uncertainty in the crude oil supply chain. The model sets inventory and orders not delivered on time as penalties and transportation costs in the objective function. The effect of demand uncertainty on supply chain returns is more significant and affects the returns from the consolidation of firms in the supply chain. Lima et al. [65] proposed a MILP model with an economic efficiency objective to determine the optimal supply chain network planning and oil distribution scheme. A fuzzy programming approach was applied to consider the effects of transportation cost and demand uncertainty in the downstream oil supply chain on the planning scenario. In another of his articles [66], a multistage stochastic programming method was proposed to solve the oil distribution problem optimally in the downstream petroleum supply chain. The time series of stochastic parameters were studied using the ARIMA method under scenario-based analysis to obtain future demand data. The proposed method effectively addresses the effect of oil price and demand uncertainty on the supply chain. Azadeh et al. [67] studied the natural gas supply chain stages from exploration, extraction, production, transportation and storage to distribution. They proposed a multi-objective, multiperiod fuzzy linear programming model to evaluate and optimise the natural gas supply chain, considering economic and environmental objectives. The model considers uncertainties in demand, capacity and cost and is solved using the possibilistic programming approach.

Mathematical uncertainty modelling for optimising oil and gas supply chain costs is evolving. An in-depth study of uncertainty in costs, storage and transportation modes can provide crucial theoretical support and practical guidance for optimising transportation decisions, reducing transportation costs and improving supply chain efficiency. For example, Zhang et al. [68] investigated and proposed a mathematical programming model of a supply chain network for synergistic biomass and crude oil collection, storage and transportation, identifying the optimal biomass storage locations and transportation modes for the studied case.

Additionally, Ghatee and Zarrinpoor [69] considered an optimisation model of facilities (e.g. oil wells, gas injection wells, production units, refineries, gas injection centres, distribution centres and terminals) to design an oil supply chain with upstream, midstream and downstream levels. The model applied optimisation objectives that included three dimensions: economic, environmental and social costs. Alizadeh and Karimi [70] proposed a two-objective MILP model for the refined petroleum supply chain. The uncertainties considered in the model included refinery and tanker inventories, transportation costs, production volumes and user demand. The solution included chance-constrained programming, scenario-based programming and P-robust optimisation methods for model solutions. Attia et al. [15] applied medium-term planning of the oil and gas supply chain in Saudi Arabia. They developed a multi-objective optimisation model that demonstrated the sustainability and environmental aspects of the planned operations and performed a sensitivity analysis to determine how the changes in the critical parameters affect the decision-making results. Figure 9 presents the influence of the output parameters on the oil and gas production by varying the price of the crude oil versus the demand.



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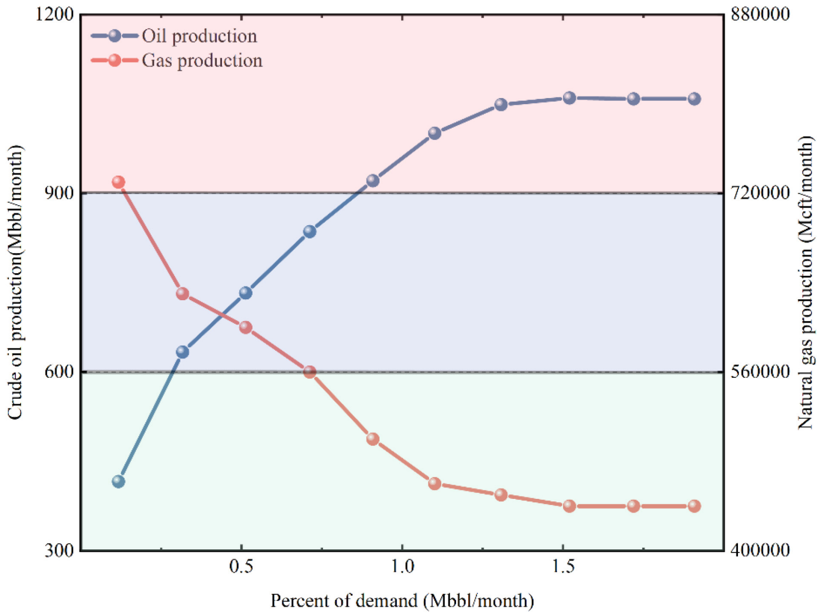

(b)

Figure 9. Crude oil prices and user demand by oil and gas production level (adapted from [15])

P-graph

P-graph was developed [71] as a tool for solving process network synthesis problems. Its primary features include graphical modelling, automatic generation of maximal superstructures, support for logical constraints, more-complete solution algorithms and a combination of network structure and goal optimisation. The graph has various application scenarios, such as energy supply chain optimisation [72], water and energy network integration optimisation [73] and municipal solid waste treatment system optimisation [74].

The P-graph is effective for process integration. In the oil and gas supply chain, the proper allocation of resources is critical, and the P-graph can graphically display relationships between links to help decision-makers identify the optimal resource allocation, improving overall efficiency and reducing costs [75]. The literature up to 2013 on using the P-graph method for supply chain and process integration in supply chain and process networks was reviewed [76]. The review concluded that the P-graph has relevant applications in supply chain integration, programming, optimisation and management and can output optimisation results quickly and intuitively. Vance et al. [72] designed a sustainable energy supply chain using the P-graph. The purpose of this supply chain is to meet the demand for electricity and heat in rural areas and recycle agricultural waste. The authors proposed a new defining indicator, "emergy," to measure the energy consumed directly and indirectly to produce products or maintain service delivery processes. This renewable energy supply chain can reduce costs by 17% compared to using a grid or natural gas for electricity generation. How et al. [77] proposed an optimisation method based on the P-graph for biomass supply chains. The method identifies the bottlenecks in the studied efficiency improvement problem in the biomass supply chain and provides the optimisation results after removing the bottlenecks. The objective function of the problem is determined using a hierarchical analysis that evaluates the three dimensions of economic, environmental and social sustainability.

In practice, optimising oil and gas supply chains often involves multiple objectives, such as minimising costs, maximising efficiency and minimising environmental effects. The P-graph can consider these objectives simultaneously and provide comprehensive solutions by constructing multi-objective optimisation models. To make the P-graph theoretical framework more convenient to apply to the actual problems of the oil and gas supply chain, one study [78] proposed a method to optimise the distribution scheme using the P-graph to optimise the supply chain of refined oil products. The method considers economic and environmental costs and quantifies the environmental costs generated during the distribution of refined oil products by pipeline, railroad and water transportation. These costs are quantified by introducing pollutant emission factors, pollutant emission costs and other indicators, reducing NOx emissions and introducing considerable environmental benefits. Kodba et al. [79] u employed a multiperiod optimisation model based on a P-graph for the biomass supply chain. The objective function of the model includes minimising the overall distribution cost and GHG emissions. In contrast, the decision-making process considers seasonal variations in biomass supply, and the input model parameters include the biomass feedstock content, biogas digester location and transportation distance.

In [80], the authors proposed an optimisation method for the energy supply chain that considers each village and town as a unit and a region containing multiple units. The top-level model optimises the regional supply chain network to minimise the carbon footprint. The second layer model takes each unit as the research object and applies the P-graph to optimise the supply chain in the unit. This method can effectively design the supply chain network to improve the utilisation efficiency of biomass energy and reduce CO_2 emissions. The P-graph provides optimisation results and visual analysis tools to help decision-makers better understand the influence of decisions on the supply chain so that they can make more scientific decisions.

The P-graph has been widely used in optimisation studies of supply chains and process networks as an effective process-integration tool. Many scholars have proposed problem-specific optimisation models using P-graphs, covering diverse fields, such as sustainable energy, biomass and oil and gas supply chains. According to the current research, it is common to propose multilevel optimisation strategies for supply chain scenarios to enhance efficiency and sustainability by considering seasonal variations, pollutant emissions and other factors in the optimisation model. Despite the many results in practical applications, exploring how to combine P-graph with other optimisation methods is still necessary to improve the solution efficiency and application breadth and provide more comprehensive and effective decision support for energy and resource management.

CONCLUSION

This paper presents an in-depth discussion of different optimisation methods from a process-integration perspective, especially for optimising oil and gas supply chains. The analysis of the existing literature revealed that multiple methods have advantages and applicability in various application fields. First, the Pinch Analysis has significant advantages in improving energy utilisation efficiency. This analysis helps decision-makers identify potential shortages or surpluses via visualisation to optimise inventory management and energy demand. Second, mathematical programming methods demonstrate flexibility and power when dealing with complex optimisation problems. These methods can determine optimal solutions under multiple constraints by constructing mathematical models. In addition, the P-graph method is an effective process-integration tool that simultaneously considers multiple objectives, such as economic, environmental and social sustainability. This approach is robust in optimising biomass and oil and gas supply chains, identifying bottlenecks, and providing visual analyses to assist decision-makers in better understanding the influence of decisions on the supply chain.

In today's increasingly complex oil and gas supply chains, integrated optimisation is performed by simultaneously considering multiple objectives and combining research results from economics, environmental science and sociology to enhance the comprehensiveness and applicability of the model. In supply chain management, process integration involves integrating the processes of suppliers, manufacturers, distributors and retailers to improve the overall efficiency of the supply chain. This work systematically identified metrics to assess supply chain optimisation in the literature on optimising supply chains. This study categorised the objectives, as indicated in **Figure 10**, and the analysis indicates that most studies have emphasised the importance of supply and demand equilibrium, optimised cost, multi-objective optimisation and sustainability. In contrast, stability and risk control have received little attention, suggesting shortcomings in the social field of supply chain optimisation research analysed from a process-integration perspective.

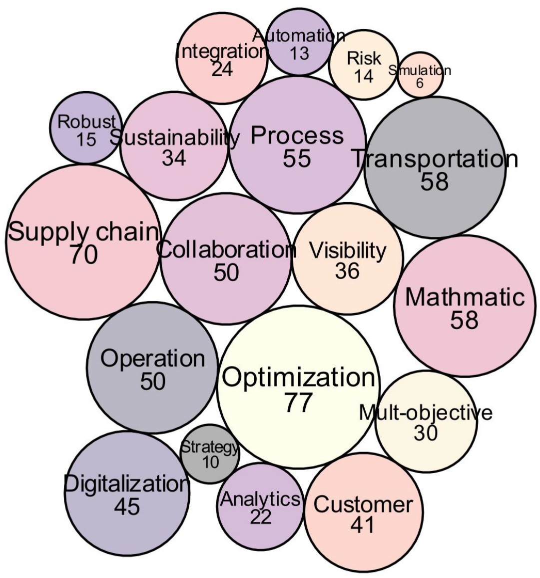

Figure 10. Frequency (%) of mentioned supply chain capabilities in the literature

With the deepening research on process integration, the existing integration methods are becoming increasingly abundant, and they gradually fit the actual optimisation problems in the oil and gas supply chain. Further research can be conducted on the following aspects of process-integration methods.

(1) With the rapid development of the oil and gas industry, efficiently solving complex optimisation problems in the oil and gas supply chain has become an important topic. Future research should focus on developing more efficient algorithms and solvers to address large-scale optimisation models.

(2) In optimisation research in the oil and gas supply chain, multiple factors (e.g. market demand fluctuations, supply chain disruptions, market prices, etc.) must be incorporated into modelling to design models closer to the actual situation. This approach can improve the accuracy of decision-making and the adaptability of the system.

(3) Internet and big data technology should be combined to research oil and gas supply chain optimisation based on real-time data. Real-time monitoring and data analysis from links in the supply chain can develop dynamic scheduling and optimisation algorithms to improve resource use efficiency and reduce operating costs.

(4) Many uncertainties exist in the oil and gas supply chain, such as price fluctuations and demand changes. In the future, research on uncertainty analysis should be strengthened to cope with uncertainty by establishing robust optimisation models, fuzzy programming models and other techniques to improve the stability and reliability of the supply chain.

(5) Combining process-integration methods with other disciplines (e.g. environmental sciences, computer sciences, etc.) for collaborative interdisciplinary research promotes the application of new methods and technology. This approach can enhance the breadth and depth of research and promote the sustainable development of the oil and gas industry.

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NOMENCLATURE

Abbreviations

IEA	International Energy Agency
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
GA	Genetic Algorithm
GRG	Generalized Reduced Gradient
ACO	Ant Colony Optimization
ARIMA	Auto Regressive Integrated Moving Average Model

REFERENCES

1. T. Zaghdoudi, K. Tissaoui, M. H. Maaloul, Y. Bahou, and N. Kammoun, ‘Asymmetric connectedness between oil price, coal and renewable energy consumption in China: Evidence from Fourier NARDL approach’, Energy, vol. 285, p. 129416, Dec. 2023, https://doi.org/10.1016/j.energy.2023.129416.
2. G. Xu, Y. Chen, M. Yang, S. Li, and K. J. S. Marma, ‘An outlook analysis on China’s natural gas consumption forecast by 2035: Applying a seasonal forecasting method’, Energy, vol. 284, p. 128602, Dec. 2023, https://doi.org/10.1016/j.energy.2023.128602.
3. H. Su et al., ‘A systematic method for the analysis of energy supply reliability in complex Integrated Energy Systems considering uncertainties of renewable energies, demands and operations’, Journal of Cleaner Production, vol. 267, p. 122117, Sep. 2020, https://doi.org/10.1016/j.jclepro.2020.122117.

4. H. Sahebi and S. Nickel, ‘Offshore oil network design with transportation alternatives’, European Journal of Industrial Engineering, vol. 8, no. 6, pp. 739–761, Jan. 2014, https://doi.org/10.1504/EJIE.2014.066936.
5. Z. Wang, S. Li, Z. Jin, Z. Li, Q. Liu, and K. Zhang, ‘Oil and gas pathway to net-zero: Review and outlook’, Energy Strategy Reviews, vol. 45, p. 101048, Jan. 2023, https://doi.org/10.1016/j.esr.2022.101048.
6. R. Qiu et al., ‘The coupling impact of subsystem interconnection and demand response on the distributed energy systems: A case study of the composite community in China’, Energy, vol. 228, p. 120588, Aug. 2021, https://doi.org/10.1016/j.energy.2021.120588.
7. A. Alnaqbi, F. Dweiri, and A. Chaabane, ‘Impact of horizontal mergers on supply chain performance: The case of the upstream oil and gas industry’, Computers & Chemical Engineering, vol. 159, p. 107659, Mar. 2022, https://doi.org/10.1016/j.compchemeng.2022.107659.
8. M. Olmez Turan and T. Flamand, ‘Optimizing investment and transportation decisions for the European natural gas supply chain’, Applied Energy, vol. 337, p. 120859, May 2023, https://doi.org/10.1016/j.apenergy.2023.120859.
9. M. Alizadeh and B. Karimi, ‘A dynamic two-phased approach for planning downstream oil supply chain network under uncertainty’, Computers & Industrial Engineering, vol. 194, p. 110374, Aug. 2024, https://doi.org/10.1016/j.cie.2024.110374.
10. S. Chen, C. Ma, W. Wang, and E. Zio, ‘An agent-based cooperative co-evolutionary framework for optimizing the production planning of energy supply chains under uncertainty scenarios’, International Journal of Production Economics, vol. 277, p. 109399, Nov. 2024, https://doi.org/10.1016/j.ijpe.2024.109399.
11. A. K. Arya, A. Kumar, M. Pujari, and D. A. de J. Pacheco, ‘Improving natural gas supply chain profitability: A multi-methods optimization study’, Energy, vol. 282, p. 128659, Nov. 2023, https://doi.org/10.1016/j.energy.2023.128659.
12. E. G. Ochieng, D. Ominde, and T. Zuofa, ‘Potential application of generative artificial intelligence and machine learning algorithm in oil and gas sector: Benefits and future prospects’, Technology in Society, vol. 79, p. 102710, Dec. 2024, https://doi.org/10.1016/j.techsoc.2024.102710.
13. H. Liu et al., ‘Research status and application of artificial intelligence large models in the oil and gas industry’, Petroleum Exploration and Development, vol. 51, no. 4, pp. 1049–1065, Aug. 2024, https://doi.org/10.1016/S1876-3804(24)60524-0.
14. S. B. Ebrahimi and E. Bagheri, ‘Optimizing profit and reliability using a bi-objective mathematical model for oil and gas supply chain under disruption risks’, Computers & Industrial Engineering, vol. 163, p. 107849, Jan. 2022, https://doi.org/10.1016/j.cie.2021.107849.
15. A. M. Attia, A. M. Ghaithan, and S. O. Duffuaa, ‘A multi-objective optimization model for tactical planning of upstream oil & gas supply chains’, Computers & Chemical Engineering, vol. 128, pp. 216–227, Sep. 2019, https://doi.org/10.1016/j.compchemeng.2019.06.016.
16. R. Qiu et al., ‘An integrated MINLP model for multi-party coordination in downstream oil supply chain’, Petroleum Science, vol. 21, no. 3, pp. 2066–2079, Jun. 2024, https://doi.org/10.1016/j.petsci.2023.12.008.
17. M. Ilyas, Z. Jin, I. Ullah, and H. Almujibah, ‘A fuzzy logic-based risk assessment framework for the crude oil transportation supply chain’, Ocean Engineering, vol. 311, p. 118997, Nov. 2024, https://doi.org/10.1016/j.oceaneng.2024.118997.
18. A. Cimino, F. Longo, G. Mirabelli, V. Solina, and P. Veltri, ‘Enhancing internal supply chain management in manufacturing through a simulation-based digital twin platform’, Computers & Industrial Engineering, vol. 198, p. 110670, Dec. 2024, https://doi.org/10.1016/j.cie.2024.110670.
19. Z. Syed and Y. Lawryshyn, ‘Risk analysis of an underground gas storage facility using a physics-based system performance model and Monte Carlo simulation’, Reliability

Engineering & System Safety, vol. 199, p. 106792, Jul. 2020, https://doi.org/10.1016/j.ress.2020.106792.
20. E. Afrifa-Yamoah, 'Towards sustainable resource management: Graph modelling insights from Ghana's oil and gas local content ecosystem', The Extractive Industries and Society, vol. 20, p. 101570, Dec. 2024, https://doi.org/10.1016/j.exis.2024.101570.
21. J. J. Klemeš and Z. Kravanja, 'Forty years of Heat Integration: Pinch Analysis (PA) and Mathematical Programming (MP)', Current Opinion in Chemical Engineering, vol. 2, no. 4, pp. 461–474, Nov. 2013, https://doi.org/10.1016/j.coche.2013.10.003.
22. M. A. Gadalla, 'A new graphical method for Pinch Analysis applications: Heat exchanger network retrofit and energy integration', Energy, vol. 81, pp. 159–174, Mar. 2015, https://doi.org/10.1016/j.energy.2014.12.011.
23. J. M. Núñez-López, J. G. Segovia-Hernández, E. Sánchez-Ramírez, and J. M. Ponce-Ortega, 'Integrating metaheuristic methods and deterministic strategies for optimizing supply chain equipment design in process engineering', Chemical Engineering Research and Design, vol. 214, pp. 93–104, Feb. 2025, https://doi.org/10.1016/j.cherd.2024.12.021.
24. B. Linnhoff, A User Guide on Process Integration for the Efficient Use of Energy, Revised, Subsequent edition. United Kingdom Institution of Chemical Engineers, Rugby, 1994.
25. X. Jia, J. J. Klemeš, S. R. W. Alwi, and P. S. Varbanov, 'Regional Water Resources Assessment using Water Scarcity Pinch Analysis', Resources, Conservation and Recycling, vol. 157, p. 104749, Jun. 2020, https://doi.org/10.1016/j.resconrec.2020.104749.
26. N. D. Chaturvedi and Z. A. Manan, 'Batch process integration for resource conservation toward cleaner production – A state-of-the-art review', Journal of Cleaner Production, vol. 318, p. 128609, Oct. 2021, https://doi.org/10.1016/j.jclepro.2021.128609.
27. M. S. Khorshidi et al., 'Integrating agent-based modeling and game theory for optimal water resource allocation within complex hierarchical systems', Journal of Cleaner Production, vol. 482, p. 144164, Dec. 2024, https://doi.org/10.1016/j.jclepro.2024.144164.
28. X. Pan, T. Shao, X. Zheng, Y. Zhang, X. Ma, and Q. Zhang, 'Energy and sustainable development nexus: A review', Energy Strategy Reviews, vol. 47, p. 101078, May 2023, https://doi.org/10.1016/j.esr.2023.101078.
29. M. Roudneshin and A. Sosa, 'A novel approach for optimisation of bioenergy supply chain: Integrating mathematical programming, Geographic Information System, and Analytic Hierarchy Process', Bioresource Technology, vol. 418, p. 131827, Feb. 2025, https://doi.org/10.1016/j.biortech.2024.131827.
30. Y. Jiao et al., 'Integration optimization of production and transportation of refined oil: A case study from China', Chemical Engineering Research and Design, vol. 188, pp. 39–49, Dec. 2022, https://doi.org/10.1016/j.cherd.2022.09.037.
31. A. Cormack, A. M. T. Thomé, and B. Silvestre, 'An integrative conceptual framework for supply chain sustainability learning: A process-based approach', Journal of Cleaner Production, vol. 320, p. 128675, Oct. 2021, https://doi.org/10.1016/j.jclepro.2021.128675.
32. H. L. Lam and W. P. Q. Ng, '21 - A Process Integration Approach for Supply Chain Development', in Handbook of Process Integration (PI) (Second Edition), J. J. Klemeš, Ed., in Woodhead Publishing Series in Energy. , Woodhead Publishing, 2023, pp. 633–657, https://doi.org/10.1016/B978-0-12-823850-9.00001-3.
33. M. Bogataj, J. J. Klemeš, and Z. Kravanja, '3 - Fifty years of Heat Integration: Pinch Analysis and Mathematical Programming', in Handbook of Process Integration (PI) (Second Edition), J. J. Klemeš, Ed., in Woodhead Publishing Series in Energy. , Woodhead Publishing, 2023, pp. 73–99, https://doi.org/10.1016/B978-0-12-823850-9.00020-7.
34. W. Chen, W. Shi, X. Li, B. Wang, and Y. Cao, 'Application of optimization method based on discretized thermal energy in condensing heat recovery system of combined heat and power plant', Energy, vol. 213, p. 119013, Dec. 2020, https://doi.org/10.1016/j.energy.2020.119013.

35. A. Singhvi and U. V. Shenoy, ‘Aggregate Planning in Supply Chains by Pinch Analysis’, Chemical Engineering Research and Design, vol. 80, no. 6, pp. 597–605, Sep. 2002, https://doi.org/10.1205/026387602760312791.
36. A. Singhvi, K. P. Madhavan, and U. V. Shenoy, ‘Pinch analysis for aggregate production planning in supply chains’, Computers & Chemical Engineering, vol. 28, no. 6, pp. 993–999, Jun. 2004, https://doi.org/10.1016/j.compchemeng.2003.09.006.
37. S. Jain and S. Bandyopadhyay, ‘Targeting segregated problems with common resources through Pinch Analysis’, Journal of Cleaner Production, vol. 301, p. 126996, Jun. 2021, https://doi.org/10.1016/j.jclepro.2021.126996.
38. R. R. Tan and D. C. Y. Foo, ‘Pinch analysis approach to carbon-constrained energy sector planning’, Energy, vol. 32, no. 8, pp. 1422–1429, Aug. 2007, https://doi.org/10.1016/j.energy.2006.09.018.
39. Z. Li, X. Jia, D. C. Y. Foo, and R. R. Tan, ‘Minimizing carbon footprint using Pinch Analysis: The case of regional renewable electricity planning in China’, Applied Energy, vol. 184, pp. 1051–1062, Dec. 2016, https://doi.org/10.1016/j.apenergy.2016.05.031.
40. S. Hwangbo, K. Nam, J. Han, I.-B. Lee, and C. Yoo, ‘Integrated hydrogen supply networks for waste biogas upgrading and hybrid carbon-hydrogen Pinch Analysis under hydrogen demand uncertainty’, Applied Thermal Engineering, vol. 140, pp. 386–397, Jul. 2018, https://doi.org/10.1016/j.applthermaleng.2018.05.076.
41. M. K. Lee, H. Hashim, W. S. Ho, Z. A. Muis, N. A. Yunus, and H. Xu, ‘Integrated spatial and Pinch Analysis of optimal industrial energy supply mix with consideration of BioCNG derived from palm oil mill effluent’, Energy, vol. 209, p. 118349, Oct. 2020, https://doi.org/10.1016/j.energy.2020.118349.
42. G. S. K. Priya and S. Bandyopadhyay, ‘Multiple objectives Pinch Analysis’, Resources, Conservation and Recycling, vol. 119, pp. 128–141, Apr. 2017, https://doi.org/10.1016/j.resconrec.2016.02.005.
43. S. Bandyopadhyay, ‘Interval Pinch Analysis for Resource Conservation Networks with Epistemic Uncertainties’, Ind. Eng. Chem. Res., vol. 59, no. 30, pp. 13669–13681, Jul. 2020, https://doi.org/10.1021/acs.iecr.0c02811.
44. M. Jalanko and V. Mahalec, ‘Supply-demand pinch based methodology for multi-period planning under uncertainty in components qualities with application to gasoline blend planning’, Computers & Chemical Engineering, vol. 119, pp. 425–438, Nov. 2018, https://doi.org/10.1016/j.compchemeng.2018.09.016.
45. L. J. Fernandes, S. Relvas, and A. P. Barbosa-Póvoa, ‘Collaborative Design and Tactical Planning of Downstream Petroleum Supply Chains’, Ind. Eng. Chem. Res., vol. 53, no. 44, pp. 17155–17181, Nov. 2014, https://doi.org/10.1021/ie500884k.
46. Y. Kazemi and J. Szmerekovsky, ‘Modeling downstream petroleum supply chain: The importance of multi-mode transportation to strategic planning’, Transportation Research Part E: Logistics and Transportation Review, vol. 83, pp. 111–125, Nov. 2015, https://doi.org/10.1016/j.tre.2015.09.004.
47. F. Montignac, D. Larrahondo Chavez, M.-C. Arpajou, and A. Ruby, ‘Assessment of hydrogen supply chains based on dynamic bi-objective optimization of costs and greenhouse gases emissions: Case study in the context of Balearic Islands’, Energy, vol. 308, p. 132590, Nov. 2024, https://doi.org/10.1016/j.energy.2024.132590.
48. J. L. Dautel, J. Thakur, and A. M. Elberry, ‘Enabling industrial decarbonization: A MILP optimization model for low-carbon hydrogen supply chains’, International Journal of Hydrogen Energy, vol. 77, pp. 863–891, Aug. 2024, https://doi.org/10.1016/j.ijhydene.2024.06.050.
49. Y. Zhou, X. Qin, W. Mei, W. Yang, and M. Ni, ‘Multi-period urban hydrogen refueling stations site selection and capacity planning with many-objective optimization for hydrogen supply chain’, International Journal of Hydrogen Energy, vol. 79, pp. 1427–1441, Aug. 2024, https://doi.org/10.1016/j.ijhydene.2024.07.067.

50. M. Li, P. Ming, R. Huo, H. Mu, and C. Zhang, 'Optimizing design and performance assessment of a sustainability hydrogen supply chain network: A multi-period model for China', Sustainable Cities and Society, vol. 92, p. 104444, May 2023, https://doi.org/10.1016/j.scs.2023.104444.
51. S. De-León Almaraz, V. Rácz, C. Azzaro-Pantel, and Z. O. Szántó, 'Multi-objective and social cost-benefit optimisation for a sustainable hydrogen supply chain: Application to Hungary', Applied Energy, vol. 325, p. 119882, Nov. 2022, https://doi.org/10.1016/j.apenergy.2022.119882.
52. F. d'Amore and F. Bezzo, 'Economic optimisation of European supply chains for CO2 capture, transport and sequestration', International Journal of Greenhouse Gas Control, vol. 65, pp. 99–116, Oct. 2017, https://doi.org/10.1016/j.ijggc.2017.08.015.
53. O. Akgul, N. Mac Dowell, L. G. Papageorgiou, and N. Shah, 'A mixed integer nonlinear programming (MINLP) supply chain optimisation framework for carbon negative electricity generation using biomass to energy with CCS (BECCS) in the UK', International Journal of Greenhouse Gas Control, vol. 28, pp. 189–202, Sep. 2014, https://doi.org/10.1016/j.ijggc.2014.06.017.
54. N. Kalyanarengan Ravi, M. Van Sint Annaland, J. C. Fransoo, J. Grievink, and E. Zondervan, 'Development and implementation of supply chain optimization framework for CO2 capture and storage in the Netherlands', Computers & Chemical Engineering, vol. 102, pp. 40–51, Jul. 2017, https://doi.org/10.1016/j.compchemeng.2016.08.011.
55. Q. Wu, Q. G. Lin, X. Z. Wang, and M. Y. Zhai, 'An inexact optimization model for planning regional carbon capture, transportation and storage systems under uncertainty', International Journal of Greenhouse Gas Control, vol. 42, pp. 615–628, Nov. 2015, https://doi.org/10.1016/j.ijggc.2015.09.017.
56. A. K. Arya, A. Kumar, M. Pujari, and D. A. de J. Pacheco, 'Improving natural gas supply chain profitability: A multi-methods optimization study', Energy, vol. 282, p. 128659, Nov. 2023, https://doi.org/10.1016/j.energy.2023.128659.
57. E.-B. Liu, Y. Peng, S.-B. Peng, B. Yu, and Q.-K. Chen, 'Research on low carbon emission optimization operation technology of natural gas pipeline under multi-energy structure', Petroleum Science, vol. 19, no. 6, pp. 3046–3058, Dec. 2022, https://doi.org/10.1016/j.petsci.2022.09.025.
58. X. Wei et al., 'Operation optimization of large-scale natural gas pipeline networks based on intelligent algorithm', Energy, p. 133258, Sep. 2024, https://doi.org/10.1016/j.energy.2024.133258.
59. D. A. Rodríguez, P. P. Oteiza, and N. B. Brignole, "Simulated Annealing Optimization for Hydrocarbon Pipeline Networks," Ind. Eng. Chem. Res., vol. 52, no. 25, pp. 8579–8588, Jun. 2013, https://pubs.acs.org/doi/abs/10.1021/ie400022g
60. A. K. Arya and S. Honwad, 'Modeling, Simulation, and Optimization of a High-Pressure Cross-Country Natural Gas Pipeline: Application of an Ant Colony Optimization Technique', Journal of Pipeline Systems Engineering and Practice, vol. 7, no. 1, p. 04015008, Feb. 2016, https://doi.org/10.1061/(ASCE)PS.1949-1204.0000206.
61. M. Mikolajková, H. Saxén, and F. Pettersson, 'Linearization of an MINLP model and its application to gas distribution optimization', Energy, vol. 146, pp. 156–168, Mar. 2018, https://doi.org/10.1016/j.energy.2017.05.185.
62. B. Wang, Y. Liang, J. Zheng, R. Qiu, M. Yuan, and H. Zhang, 'An MILP model for the reformation of natural gas pipeline networks with hydrogen injection', International Journal of Hydrogen Energy, vol. 43, no. 33, pp. 16141–16153, Aug. 2018, https://doi.org/10.1016/j.ijhydene.2018.06.161.
63. J. Zhou et al., 'Automatic response framework for large complex natural gas pipeline operation optimization based on data-mechanism hybrid-driven', Energy, vol. 307, p. 132610, Oct. 2024, https://doi.org/10.1016/j.energy.2024.132610.

64. A. Alnaqbi, J. Trochu, F. Dweiri, and A. Chaabane, ‘Tactical supply chain planning after mergers under uncertainty with an application in oil and gas’, Computers & Industrial Engineering, vol. 179, p. 109176, May 2023, https://doi.org/10.1016/j.cie.2023.109176.
65. C. Lima, S. Relvas, and A. Barbosa-Póvoa, ‘Designing and planning the downstream oil supply chain under uncertainty using a fuzzy programming approach’, Computers & Chemical Engineering, vol. 151, p. 107373, Aug. 2021, https://doi.org/10.1016/j.compchemeng.2021.107373.
66. C. Lima, S. Relvas, and A. Barbosa-Póvoa, ‘Stochastic programming approach for the optimal tactical planning of the downstream oil supply chain’, Computers & Chemical Engineering, vol. 108, pp. 314–336, Jan. 2018, https://doi.org/10.1016/j.compchemeng.2017.09.012.
67. A. Azadeh, Z. Raoofi, and M. Zarrin, ‘A multi-objective fuzzy linear programming model for optimization of natural gas supply chain through a greenhouse gas reduction approach’, Journal of Natural Gas Science and Engineering, vol. 26, pp. 702–710, Sep. 2015, https://doi.org/10.1016/j.jngse.2015.05.039.
68. S. Zhang, Q. Lei, L. Wu, Y. Wang, L. Zheng, and X. Chen, ‘Supply chain design and integration for the Co-Processing of bio-oil and vacuum gas oil in a refinery’, Energy, vol. 241, p. 122912, Feb. 2022, https://doi.org/10.1016/j.energy.2021.122912.
69. A. Ghatee and N. Zarrinpoor, ‘Designing an oil supply chain network considering sustainable development paradigm and uncertainty’, Chemical Engineering Research and Design, vol. 184, pp. 692–723, Aug. 2022, https://doi.org/10.1016/j.cherd.2022.06.026.
70. M. Alizadeh and B. Karimi, ‘A trio of resiliency, reliability, and uncertainty to design and plan the downstream oil supply chain’, Computers & Chemical Engineering, vol. 176, p. 108281, Aug. 2023, https://doi.org/10.1016/j.compchemeng.2023.108281.
71. V. Varga, I. Heckl, F. Friedler, and L. Fan, ‘PNS Solutions: a P-Graph Based Programming Framework for Process Network Synthesis’, Chemical Engineering Transactions, vol. 21, Jan. 2010, https://doi.org/10.3303/CET1021232.
72. L. Vance, I. Heckl, B. Bertok, H. Cabezas, and F. Friedler, ‘Designing sustainable energy supply chains by the P-graph method for minimal cost, environmental burden, energy resources input’, Journal of Cleaner Production, vol. 94, pp. 144–154, May 2015, https://doi.org/10.1016/j.jclepro.2015.02.011.
73. H. H. Chin, D. C. Y. Foo, and H. L. Lam, ‘Simultaneous water and energy integration with isothermal and non-isothermal mixing – A P-graph approach’, Resources, Conservation and Recycling, vol. 149, pp. 687–713, Oct. 2019, https://doi.org/10.1016/j.resconrec.2019.05.007.
74. Y. V. Fan, J. J. Klemeš, T. G. Walmsley, and B. Bertók, ‘Implementing Circular Economy in municipal solid waste treatment system using P-graph’, Science of The Total Environment, vol. 701, p. 134652, Jan. 2020, https://doi.org/10.1016/j.scitotenv.2019.134652.
75. Á. Orosz, P. S. Varbanov, J. J. Klemeš, and F. Friedler, ‘Process synthesis considering sustainability for both normal and non-normal operations: P-graph approach’, Journal of Cleaner Production, vol. 414, p. 137696, Aug. 2023, https://doi.org/10.1016/j.jclepro.2023.137696.
76. H. L. Lam, ‘Extended P-graph applications in supply chain and Process Network Synthesis’, Current Opinion in Chemical Engineering, vol. 2, no. 4, pp. 475–486, Nov. 2013, https://doi.org/10.1016/j.coche.2013.10.002.
77. B. S. How, T. T. Yeoh, T. K. Tan, K. H. Chong, D. Ganga, and H. L. Lam, ‘Debottlenecking of sustainability performance for integrated biomass supply chain: P-graph approach’, Journal of Cleaner Production, vol. 193, pp. 720–733, Aug. 2018, https://doi.org/10.1016/j.jclepro.2018.04.240.
78. B. Wang, Y. V. Fan, H. H. Chin, J. J. Klemeš, and Y. Liang, ‘Emission-cost nexus optimisation and performance analysis of downstream oil supply chains’, Journal of Cleaner Production, vol. 266, p. 121831, Sep. 2020, https://doi.org/10.1016/j.jclepro.2020.121831.
79. A. Kodba, T. Pukšec, and N. Duić, ‘P-Graph approach for the economical optimisation of biomass supply network that meets requirements on greenhouse gas emissions savings - A case

study of rural areas', Journal of Cleaner Production, vol. 416, p. 137937, Sep. 2023, https://doi.org/10.1016/j.jclepro.2023.137937.

80. H. L. Lam, P. S. Varbanov, and J. J. Klemeš, 'Optimisation of regional energy supply chains utilising renewables: P-graph approach', Computers & Chemical Engineering, vol. 34, no. 5, pp. 782–792, May 2010, https://doi.org/10.1016/j.compchemeng.2009.11.020.

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