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# Maintenance in the downstream petroleum industry: A review on methodology and implementation

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ABSTRACT

This paper presents a literature review on maintenance operations in the downstream petroleum industry. This process industry comprises facilities ranging from processing units to distribution networks, which makes the maintenance activities diverse. Maintenance optimization approaches from over 120 articles have been organized into two broad categories. The first category implemented maintenance operations according to the criticality of equipment by applying methods like American Petroleum Institute, Analytical Hierarchy Process, and Failure Modes and Effect Analysis. The second category applied various optimal policies by adopting different tools such as mathematical models (probability, statistics, linear or nonlinear optimization methods, fuzzy logic), heuristic (metaheuristics) algorithms (genetic algorithm, firefly algorithm), data analytics (machine learning), and Internet of Things. The review also included maintenance implementation frameworks, planning & scheduling methods, safety, mechanization, and evaluation procedures. It also tracks the recent trends in the maintenance implementation approach, identifies gaps, and recommends future research directions.

## 1. Introduction

The petroleum industry can be broadly divided into three categories (see Fig. 1): Upstream, Mid-Stream, and Downstream (Clews, 2016). The upstream section mainly focuses on crude oil or natural gas production. The mid-stream section consists of the logistic system that links the upstream and downstream sections, including pipelines, ships, ports, and different storage facilities. The downstream section of the industry focuses on crude oil refining, natural gas processing, the petrochemical industries that process products derived from the refineries (the natural gas processes), and the distribution of final products to consumers (Iqbal et al., 2017). This last section of the industry integrates different and complex equipment that requires a variety of maintenance policies for a profitable run. This review paper presents component/equipment criticality analysis procedures, maintenance policy optimization methodology, and other maintenance-related studies on the downstream section of the petroleum industry from the literature.

The transformation of crude oil or natural gas into consumable products involves several processes. Crude oil processing involves separation (heating the crude oil and collecting the different products at their respective boiling temperature), conversion (converting the outputs of the separation process into consumable products), and treatment (ensuring product consistency of final products) (US Energy Information Administration 2022). These processes require different storage facilities, equipment (for processes like distillation and cracking), utilities, waste treatment processes, and internal transportation systems. Natural gas processing primarily involves removing unwanted components such as water, oil, nonhydrogen gas, and different contaminants (US Energy Information Administration 2022). Several processes are involved in natural gas processing, including separation, dehydration, and extraction of different gasses. The final consumable products also require different types of facilities for distribution. Some of the by-products of refineries or the natural gas processes (referred to as feedstock) are supplied to the petrochemical industries for further processing. These industries process the input from the oil (gas) industries to produce consumer goods like plastics, synthetic rubber, fibers, fertilizers, dye, surfactants, and detergents. The by-products from refineries (natural gas processing) require some intermediate processes before the petrochemical industries convert them into finished goods (Clews, 2016). These include the *Building Blocks* process and the *Intermediate Chemicals* process.

Maintenance is one of the most critical functions for the profitability

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of any company in the downstream petroleum industry. It affects costs related to production interruption, unsafe working conditions, environmental degradation, and product quality losses due to poorly maintained facilities. The maintenance operations also incur financial costs through acquisitions of spare parts, repair equipment, inventory expenses, and labor wages. Furthermore, companies can have a large volume of equipment requiring maintenance (which varies in frequency and severity) over their service life. The importance or criticality of each production equipment could also differ amongst facilities. Hence, companies would have to prioritize their maintenance activities for each piece of equipment. This requires maintenance optimization methods to address these complex prioritization processes in order to determine the optimal policy to service every piece of equipment. The objective of these optimizations could be to maximize profitability, improve production safety or reliability of equipment, and/or minimize cost.

Various maintenance policies can be found in the literature. These policies can be categorized into two broad groups based on the activities performed: corrective and preventive maintenance.

- Corrective maintenance (CM) is defined as a repair operation to failed equipment (Ben-Daya et al., 2016). The operations can consume a large volume of resources and take a long time complete. Low-cost and non-critical equipment/components can adopt this policy to minimize maintenance costs and resource requirements.
- Preventive maintenance (PM) includes all operations to minimize failure rates and severity. These operations are initiated based on different factors that, in most cases, are used to frame the maintenance policy (Ben-Daya et al., 2016). Some of these policies have been briefly described below.
- *Time-based maintenance* is performed over a predefined time interval or number of usage. Equipment can be maintained at different time intervals. Productions are halted for a short period at a predetermined interval to perform maintenance on multiple pieces of equipment (referred to as turnaround maintenance).
- *Reliability-centered* employs the deterioration rate of equipment in order to determine the maintenance operation based on an acceptable risk level. When this level is surpassed, reliability-centered maintenance is initiated.
- *Predictive maintenance* applies various equipment/component deterioration data collection methods to predict and then carry out maintenance operations. Data-driven methods have been widely used in this method.
- *Condition-based maintenance* is performed after inspecting the equipment's operational state to prevent future failures. The inspection can be performed continually or on a timely basis.
- *Risk-based inspection and maintenance* policy utilize the risk level of equipment to propose a maintenance priority for a group of equipment or system. The maintenance policy focuses on reducing the risks that arise from equipment failure. In this policy, risk computation can extend to broader factors that are generally not considered under most maintenance policies.
- *Opportunistic maintenance* is defined as unplanned machinery restoration operations during production shutdown due to the above-mentioned maintenance policies (Chin et al., 2020).
- *Failure and fault-finding maintenance* operations focus on equipment used intermittently, where the equipment was maintained right before its subsequent use.

This paper reviewed articles on the optimal implementation of maintenance operations in the downstream petroleum industry. The main concepts of the different approaches from the literature are organized into two broad categories in the paper. In the first category, articles assess the criticality of components, equipment, or systems that were used to guide an optimal maintenance operation. Some of the assessment methods adopted include American Petroleum Institute (API) guide, Analytical Hierarchy Process (AHP), and Failure Modes and Effect Analysis (FMEA). In the other category, articles implement optimal maintenance policies. Frequently implemented policies comprise turnaround, risk-based, predictive, reliability-based, condition-based, or some combinations of these policies. The optimization decision variables of maintenance operations have mandated the use of mathematical tools like probability, statistics, linear programming, nonlinear programming, Markov decision process, fuzzy logic; machine learning; Internet of Things; and heuristic (metaheuristic). Other maintenance-related subjects in the downstream petroleum industry have also been reviewed in this paper to provide a complete picture of the function. These included maintenance scheduling, safety, sustainability, and mechanization. A few articles have highlighted implementation frameworks for the various maintenance operations in the downstream petroleum industry, while others proposed procedures for the evaluation of operations.

The remainder of this paper is organized as follows. Section 2 presents some general background on the maintenance activities in the downstream petroleum industry. The methods for collecting and organizing the reviewed articles are also presented in this section. Section 3 covers the details of the reviewed articles. These articles are organized into different subsections to examine the maintenance approaches systematically. Numerical analyses of the reviewed articles as well as a brief discussion, are given in Section 4. Future research directions, supported by reference articles, are proposed in Section 5. The final section presents concluding remarks.

## 2. Background

The downstream petroleum industry mainly processes the final products and distributes them to the consumers. The processing section comprises product and by-product processing, whereas the distribution section encompasses different pipeline networks, tanker trucks (trains), storage facilities, pumping stations, and retail stations. The production process and the distribution section for most parts of the industry are continuous processes. Therefore, the maintenance operations may not be performed without shutting down (at least reducing production

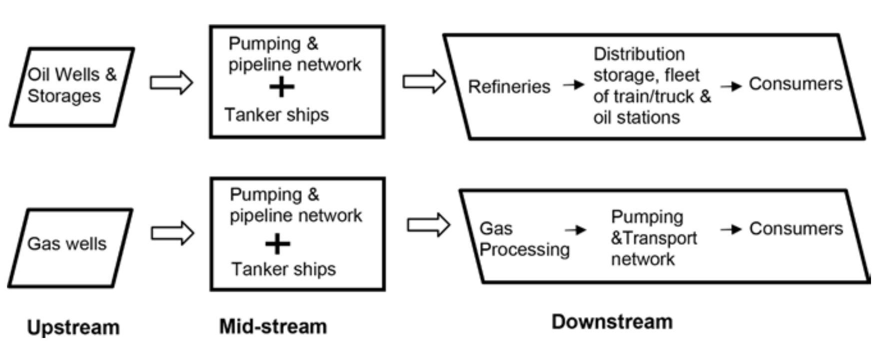


**Fig. 1.** Oil – Natural Gas processing.

capacity) the whole facility in most cases. In these cases, turnaround maintenance is commonly applied to complete maintenance operations. Condition- and reliability-based approaches can be used for critical components/equipment to determine the shutdown/scale-down period, and opportunistic maintenance can be adopted for the remaining equipment. The degradation rate can be computed using a stochastic method that utilizes a probability distribution for the specific equipment. The direct and indirect maintenance costs would have to be compared among the various alternatives before deciding on the specific preventive maintenance policy or resorting to the traditional corrective maintenance policy. Equipment for transportation (including vehicles), storage, and retail stations can adopt any of the preventive maintenance approaches discussed above. For example, time-based maintenance for vehicles and condition-based or reliability-centered maintenance for storage and retail stations can be regarded as more suitable approaches. Factors like the equipment's or component's criticality, government-imposed safety regulations/laws, and the manufacturer's mandatory inspection and repair operations can be integrated into the policy optimization efforts.

Maintenance management involves planning, policy adoption, and effectiveness & efficiency assessment activities (Ruschel et al., 2017). Planning can include scheduling operations and integrating different organizational functions, production systems, and supply chains. Selecting and adopting the appropriate policy addresses issues related to modeling the degradation process, inspection/maintenance intervals, operational cost estimation, and service life management of equipment. The assessment activities incorporate health prognosis, analysis of reliability, risk, and consequence, along with monitoring and evaluating operations. These activities entail optimization tools to tackle the scarcity of different resources and limitations of policies. Optimization requires a model formulation for the problem with a specific objective/s and a solution method to solve the model. Solving these optimization models is challenging because of the large volume and variety of equipment/components needed in the computation. It is further complicated by the imprecise and often dynamic nature of the data collected for analysis.

This paper selected articles directly relevant to the downstream petroleum industry to provide a focused analysis. The articles were searched based on the following phrases:

1) "Petrochemical, refinery, oil & gas, pipeline, and distribution network, tanker truck," which represented subsectors in the downstream petroleum industry;
2) "maintenance, combined/joint maintenance, and spare part optimization, preventive, risk-based, condition-based, turnaround" for searching maintenance policies;
3) "maintenance framework, and maintenance evaluation" for searching implementation procedures and assessment tools for the overall maintenance operations.

The filtering processes were performed on the title of the articles (Chin et al., 2020) over multiple stages. Upon careful inspection, a few articles have been dropped off because of the lack of direct relation to the downstream petroleum industry. Google Scholar was the main search engine used to identify the articles on the subject matter. As a result, 120 articles were collected, organized, and then presented under different categories, with a brief discussion of each article. Fourteen more papers have been presented to benchmark the recent developments in maintenance optimization in other industries.

## 3. Literature review

The maintenance function optimization followed two directions: methods centered on equipment criticality assessment (independently) or the optimization of the maintenance policy. The first direction concentrated on equipment criticality to perform maintenance operations (covered in Section 3.1). The second direction applied maintenance optimization based on different policies, which may integrate the criticality assessments (covered in Section 3.2). Optimization methods can also consider different objectives, such as implementation planning/scheduling and multiple organizational functions. In addition, other maintenance implementation topics have also been reviewed in this section (covered in Section 3.3). The presentation of reviewed articles followed this organization. The industrial processing order (oil and gas processing, distribution, and by-product process) was used to organize the presentation at the lowest level. Fig. 2 summarizes the maintenance operation optimization in the downstream petroleum industry.

### 3.1. *Criticality assessment methods*

Criticality assessment of equipment (components) is very crucial to efficiently utilize the limited maintenance resources. When a large amount of equipment is considered for maintenance (often the case for the downstream petroleum industry), optimizing specific objective/s may not be practical. Criticality assessment effectively isolates the essential or non-essential equipment/components to allocate the appropriate level of attention. Assessments can be based on several factors, such as importance to the processes, repair cost, level of degradation, reliability, safety to the production process and society, and impact on the environment. Table 1 summarizes the articles that implemented these methods, which are discussed in the section.

One of the most widely used methods for determining the equipment's criticality was developed by American Petroleum Institute (API), which applied a risk-level assessment method. The risk level of equipment was computed as a product of the likelihood of failure (LOF) and consequence of failure (COF). LOF may include failure frequency, likelihood factors like age, working environments and inspection proficiency, and management system. COF consisted of availability and maintenance cost, accident and injury, and environmental impact. The methods employed for estimating the LOF and COF distinguished the various approaches observed in the literature.

Analytical hierarchy process (AHP) and failure modes and effect analysis (FMEA) have also been adopted for criticality assessment. AHP is a method where risk factors are compared among themselves for each piece of equipment/component. Weights are given to each factor based on its criticality. The FMEA approach integrates experts' analysis of different risk factors. AHP and FMEA approaches have also been used in conjunction with policy optimization, and several articles were cited in the following subsections to demonstrate this application in the downstream petroleum industry.

Other criticality assessment methods have also been adopted in the industry. These methods combined the API, AHP, and FMEA methods with methods like fuzzy logic, critical indexing, and quality function deployment (QFD). Novel approaches such as Pareto analysis, machine learning, robust portfolio model, self-organizing map, and heuristic have also been implemented.

#### 3.1.1. *Inspection operations*

The criticality assessment method has been implemented to prioritize the inspection operations of equipment in the industry. (Choi et al., 2005) used API standard methods to compute the risk level of equipment to determine the inspection management and reinspection intervals based on production data for refineries. It considered factors like mechanical and processing environments, failure frequency, and equipment management as input for LOF, whereas financial risk (equipment failures, production interruption, injuries compensation, environmental cleanup) as factors for COF for a case from the refineries. Chang et al. (Chang et al., 2005) focused on directly applying the methods to the pipings by considering management, failure frequency, and likelihood (age, damage mechanisms/frequencies, inspection proficiency) for LOF computation, whereas injury compensation, environment cleanup, adjacent repair, and downtime factors for COF. Tien et al. (2007)

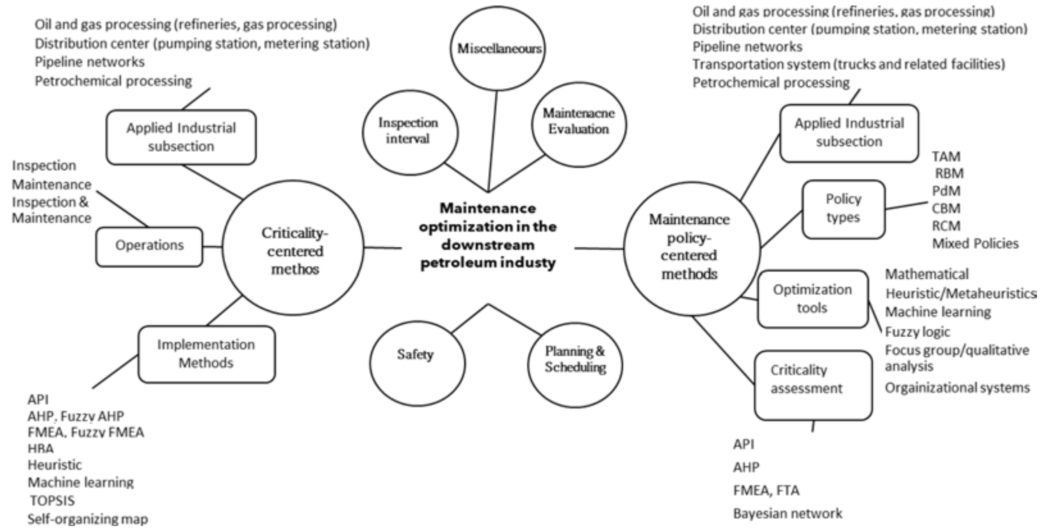


**Fig. 2.** Maintenance optimization approaches summary for the downstream petroleum industry.

demonstrated the API implementation using the facility's data to formulate the LOF (based on piping, damage, inspection, condition, process, and mechanical factors) and COF (based on chemical, quantity, state, escalation, pressure, credit, damage potential, toxic quantity, dispersibility, population, credit factors). Filho et al. (Filho et al., 2004) used the API approach to calculate the probability of failure to prepare an inspection plan for a pipeline network. When computing the damage (as part of the causes for failure), a Bayesian-based approach was used to update the current conditions of the pipes based on the latest inspection results and prior state. Mokhtar, Ismail, & Muhammad (Mokhtar et al., 2009) compared degradation analysis and first-order reliability methods for computing failure probability. These methods computed the API failure likelihood using failure probability drawn from the risk-based inspection data for a pipe system. Degradation analysis was built on probability distribution fitted to the data collected, whereas the first-order reliability method implemented an optimization program for material property and physical geometry data. Shuai et al. (2012) and Zhang et al. (Zhang et al., 2017) have presented API implementation to determine the inspection management method before executing risk reduction measures for the facilities. The LOF was computed as the probability of failure at a given time (a function of the generic failure frequency, management system, and equipment factor). Financial-based consequences were considered as COF. Wang et al. (Wang et al., 2014) implemented a failure rate computation method using Monte Carlo simulation to determine the failure rate. The failure rate was adjusted using the damage factor (considering active damage mechanism and historical inspection data) before being applied as LOF for computing the API.

### 3.1.2. *Maintenance operations*

The API method has also been adopted to determine the criticality of maintenance operations. Anvaripour et al. (Anvaripour et al., 2013) employed the Delphi method (a method for collecting data by surveying a group of experts) to analyze API risk levels and categorize refinery assets. Failure frequency was considered as LOF, while the COF was computed as the product of operational impact, flexibility, maintenance cost, and impact on safety and environment. Bevilacqua et al. (Bevilacqua et al., 2016) compared the risk-based (using API) and criticality index (based on different process parameters) approaches to predict maintenance needs for the main processing equipment. The critical index method computed the risk level by adding the weighted values of several factors (temperature, pressure, complexity, available backups, effect and occurrence of failures, accidents, environments, and so on). Bevilacqua & Braglia (Bevilacqua and Braglia, 2000) presented an AHP-based maintenance optimization model, which includes damages, applicability (in terms of investment cost and technical feasibility), added value, and cost of maintenance. Rahmana (Rahmana et al., 2021) adopted an approach combining quality function deployment (QFD) with AHP and FMEA (added for risk analysis). QFD is a method developed for gathering information on customers' requirements as well as the level of satisfaction for a given product or service. Wang et al. (Wang et al., 2012) adopted the FMEA-based method to compute the criticality of a failure based on safety, environmental impact, and economic loss using a panel of experts. It integrated API to compute the risk levels and AHP to determine the importance of the failure factor for a case from a catalytic reforming plant.

A few articles have incorporated fuzzy logic approaches to the AHP for determining the criticalities of a range of equipment in a facility (components in a system). This approach enabled the formulation of different value levels for parameters that have been used to assess the criticality level. Shahri et al. (2021) integrated a fuzzy inference system with AHP for assessing the criticality of assets from the gas processing plant. The risk level of an asset was calculated using a weighted probability & consequence of failure criteria then an AHP was used to prioritize the criteria (determined by a panel of experts). The fuzzy inference system analyzed failure criteria to establish the asset's criticality for implementing maintenance operations. Mohamed and Saad (2016) proposed a fuzzy AHP where a multi-criteria decision model (a hierarchy of criteria) was developed to evaluate equipment. Data for safety, cost, reliability, and availability factors were collected first, then a fuzzy AHP method (Eigenvalue method (EVM), mean normalized value (MNV), and normalized geometric mean (NGM) - details given in Saad et al. (2016) was implemented to determine the priority. The factors determined the mode-based maintenance policy.

Laggoune and Aïssani (2000) implemented Pareto analysis to determine the rankings of machines used for maintenance decision-making. Then a reliability distribution function was fitted to study the failure property of high-priority equipment and propose the appropriate maintenance policy. Pareto analysis determines the major causes of failures. According to the theory, 80% of the failures can be attributed to 20% of the causes. Astepe and Alkara (2021) presented a machine learning tool to prioritize maintenance operations. The model automated the prioritization process through machine learning algorithms, including logistic regression, support vector machine classifier, artificial neural networks, random forests, LightGBM (Light Gradient Boosting Machine) classifier, and XGBoost (Extreme Gradient Boost) classifier.

For a pipeline distribution network, Cagno et al. (2000)

**Table 1**
Summary of criticality assessment methods.

| Operations | Application Subsector | Assessment Method | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|---|
| Inspection | Refinery | API based approach | [1]A:- well-defined mathematical formulation.- documented standard procedure. | Choi et al. (2005); |
| | Pipeline network | API based approach | | Chang et al., 2005; Tien et al. (2007); Filho et al. (2004) Mokhtar et al. (2009) |
| | Crude oil tanks; Gas compressor stations | API based approach | D:- no procedures for component comparison. | Shuai et al. (2012); Zhang et al. (2017) |
| | Petrochemical | API based approach | | Wang et al. (2014) |
| Maintenance | Refinery | API based approach | | Anvaripour et al. (2013) |
| | | API & Critical Index | | Bevilacqua et al. (2016) |
| | | AHP | [2]A:- expert's or customer's input and comparison procedure included. | Bevilacqua & Braglia, (2000) |
| | | QFD, AHP, FMEA | | Rahmana (2021) |
| | | Pareto analysis | | Laggoune & Aïssani (2000) |
| | | | D:- vary organizations-wise. | |
| | Catalytic reforming plant | FMEA, API, AHP | | Wang et al. (2014) |
| | Gas Processing | Fuzzy AHP | [3]A: consider uncertainty | Shahri et al. (2021) |
| | | | D: complex formulation | |
| | Petroleum industry | Fuzzy AHP | | Mohamed and Saad (2016) |
| | Oil and Gas industry | Machine learning | A: data-based approach | Astepe and Alkara (2021) |
| | Oil & gas pipeline | Fuzzy Machine learning | D: factor's details are hidden | Yin et al. (2021) |
| | Pipeline network | AHP | 2 . | Cagno et al. (2000) |
| | Gas distribution network | Robust portfolio model (RPM) | | Sacco et al. (2019) |
| | Natural Gas Regulating and Measuring Station (NGRMS) | Hierarchical Bayesian Approach (HBA) | | Leoni et al. (2021a); Leoni et al. (2021b); Leoni et al. (2020) |
| | Petrochemical | API based approach | 1 . | Jaderi et al. (2014) |
| | | Fuzzy FMEA | 3 . | Guo et al. (2009) |
| | | TOPSIS | | Guevara et al. (2019) |
| | | Self-organizing map, GA | A: applied to large number of component | F. Jaderi et al. (2019) |
| Inspection & Maintenance | Refinery | Procedural heuristics | | Bertolini et al. (2009); Bevilacqua et al. (2012) |
| | | | D: factor's details are hidden | |
| | Petrochemical | API based approach | 1 . | Choi et al. (2007) |
| | | AHP, Resistive maintenance | 2 . | Hosseini et al. (2021) |
| Safety; Maintenance | Ammonium Hydroxide Production Unit | API and AHP approach | 1 . | Ghasemi et al. (2021) |

demonstrated the implementation of Bayesian inference to combine expert opinions (using AHP) with historical data to improve the failure probability estimation. The estimate, combined with the length of the section and standard replacement period, has enabled the prioritization of replacement activities. Yin et al. (2021) proposed a fuzzy logic inference method combined with machine learning algorithms to determine the failure criticality of the oil and gas pipeline. The fuzzy inference was applied to evaluate failure criticality factors (safety, flow interruption effect, environmental impact, maintenance), while the machine learning part was used to construct a maintenance predicting model. The machine learning consisted of multilayer perceptron, support vector regression, and random forest algorithms. Sacco et al. (2019) developed a robust portfolio model (RPM) to identify maintenance decisions that effectively reduce the likelihood and severity of failures. RPM methods are considered effective in cases where there is incomplete knowledge about parameters or imprecise decision-maker preferences. It uses weighted values for evaluating different criteria. The model was used to construct a maintenance framework based on a pipeline's internal corrosion, external corrosion, and other related activities. Leoni et al. (2021) compared three risk-based criticality assessment methodologies: a combined hierarchical Bayesian network and FMECA (HBN-FMECA) method (with data collection, probability and severity analysis, and risk analysis stages), quantitative risk analysis using Safeti software (with hazard definition and scenario identification, rate estimation, consequence evaluation, and risk level determination steps), and risk-based inspection plan using Synergi Plant(with collecting equipment and evaluation data, then risk analysis steps). The failure mode, effect, and criticality analysis (FMECA) were performed on the component to assess the severity of the failure to determine priorities. FMECA is a more in-depth analysis of criticality based on an extension of the FMEA method. Leoni et al. (Leoni et al., 2021) adopted the HBN method to compute the failure probability, while the FMECA method was used to calculate the severity of the failure. Markov chain Monte Carlo simulation was incorporated into the HBN to address any change or uncertainty associated with input data. The cost of failure was estimated in order to determine the risk level. Leoni et al. (Leoni et al., 2020) compared a combined HBN, FMECA, and cost risk priority number (CRPN) method with the quantitative risk analysis (QRA) method to prioritize the maintenance activities of components for a case from natural gas regulating and metering station. Using standard probabilities, QRA was used with software (Safeti) for rapture and leakage scenarios. The HBN method estimated the probability of failure, while FMECA assessed the failure's severity, and the CRPN assigned the priority for maintenance.

Jaderi et al. (2014) presented an API risk-based criticality assessment method for the petrochemical industry, considering factors like failure frequency, operational impact & flexibility, maintenance cost, and environmental impact. Guo et al. (2009) formulated criticality based on different factors (production loss, safety effect, maintenance cost, and environmental impact) for a similar industry. The model was evaluated using an FMEA combined with a fuzzy back-propagating neural network method. Guevara et al. (2019) demonstrated the implementation of a technique for order preference by similarity to ideal solution (TOPSIS) to plastic mold machinery. TOPSIS method evaluates equipment based on multiple criteria where the best (ideal) value for each criterion is used as a reference point for measurement. In this article, the TOPSIS approach ranked machines (based on five evaluation criteria), followed by implementing the maintenance operations based on the rankings. Jaderi (F. Jaderi et al., 2019) presented a combined self-organizing feature map and genetic algorithm (GA) approach to assess equipment's vulnerability and determine maintenance priority. The approach considered the operational impact and flexibility, cost, the impact on safety & environment, and the frequency as parameters in the analysis of the components. A self-organizing network was used to assess equipment risk based on the parameter. GA was used to optimize the structures of the system's network.

#### 3.1.3. Combined inspection and maintenance operations

Bertolini et al. (Bertolini et al., 2009) and Bevilacqua et al. (Bevilacqua et al., 2012) proposed a procedural (heuristic) approach that assessed the criticality of equipment in a refinery. Bertolini et al. (2009) presented a procedure that considered five probability classes and four severity categories (i.e., safety, environmental, economics, and reputation) for computing a risk matrix using a panel of experts. The procedure by Bevilacqua et al. (Bevilacqua et al., 2012) includes listing components (with their relevant information), assigning risk factors, filtering components (using a computerized maintenance management system), and determining the criticality of these items. The proposed method was shown to perform better compared to risk-based maintenance approaches. Choi et al. (2007) used equipment data and different operating scenarios to compute the API risk level (using Korean Gas Safety – RBI software or KGS-RBITM). The inputs for the software included equipment description data, consequence data (like material, fluid state, toxic material, detection rate), likelihood data (like the number of valves, branches, injection points and connections, vibration monitoring, construction), and financial data. Hosseini, Shahanaghi, & Shasfand (Hosseini et al., 2021) proposed an AHP method based on expert opinions. The method introduced a maintenance index based on the strength, opportunities, and sustainability against weaknesses and threats. Several indicators were used to formulate the index: equipment type, cost and labor effectiveness, economic impact, and compliance with safety and environmental regulations. Ghasemi, Azimi, & Ghasemi (Ghasemi et al., 2021) proposed a combined API-AHP method for a criticality analysis to implement maintenance priorities for an Ammonium Hydroxide Production Unit. The risk levels were determined using the API, whereas the AHP was used to select the appropriate maintenance policy based on multiple criteria (safety, cost, feasibility).

### 3.2. Maintenance policy optimization

Maintenance policies optimization concentrates on the optimization of resources utilized under given maintenance policies for predefined objective(s). This subsection discusses the implementation of these policies, including framework/guides, research reviews, and implementation varieties. However, the main focus will be the optimization methods for implementing the policy. Optimization tools have been developed from several fields of study (including operation research, mathematics, statistic, machine learning, and network analysis). These tools follow diverse approaches that have been summarized to illustrate the implementation procedures under each policy. Few methods integrated the criticality assessment methods discussed above (Section 3.1) as part of the optimization model. Others combined multiple policies to fit specific problems better (see subsection *d*). Other related objectives were studied when policies were not optimized, which have been covered in the subsequent subsection (Section 3.2).

#### 3.2.1. Turnaround maintenance

Most refineries and natural gas processing plants apply turnaround maintenance (TAM) to perform extensive maintenance activities. Determining the optimal time for the maintenance activities is crucial because the production process will be ceased during these activities. All maintenance activities are restricted to completion within a given time frame so normal production can resume. Although external factors (such as market demand, availability of spare parts, and/or skilled labor and weather condition) affect the schedule, the assessment of maintenance requirements is the main factor that determines the schedule. Different assessment methods have been proposed in the literature, which would be the focus of this section (Table 2).

As an overall guide, Al-Turki et al. (2019) presented a review on the implementation (initiation, preparation, execution, and termination) of TAM for processing industries (including refineries and petrochemical industries). The management of maintenance operations included schedule optimization, risk management, collaboration, and information (knowledge, best practices) sharing over the supply chain. Pokharel and Jiao (2008) and Johansson and Rudberg (2010) presented different case studies on implementing TAM approaches in different organizations. These publications emphasized a holistic (including external parties) and continuous approach to maintenance management. Pokharel & Jiao (Pokharel and Jiao, 2008) reviewed the planning activities like maintenance team formation, scope formulation, and shutdown optimization (using software), while the implementation focused on the events observed on the ground. Johansson & Rudberg (Johansson and Rudberg, 2010) studied the implementation of maintenance based on an eight-phase maintenance framework from the literature on three industrial cases (refer to Crespo Márquez et al. (Crespo Márquez et al., 2009) for the details of the framework). The phases are defining objectives, priority & strategy definitions, intervention, planning, scheduling (optimizing), execution, life cycle analysis, and continuous improvement. The article evaluated the maintenance activities from the perspective of holistic maintenance's effectiveness, efficiency, and assessment. Almomani & Aldaihani (Almomani and Aldaihani, 2020) presented a maintenance operation management system based on equipment availability. The article described a zero-shutdown preventive maintenance policy that incorporated activities such as equipment identification and evaluation (whether it can be maintained without shutdown or affecting production), defining pre- and post-shutdown maintenance tasks, and determining shutdown focus operations (review, temporary by-pass solution, and project activities). Elwerfalli, Khan, & Munive-Hernandez (Elwerfalli et al., 2018) presented an improved scheduling model which comprised of removing non-critical equipment, implementing a risk-based inspection of critical equipment, and classifying & determining the failure rate. Failure causes were identified using the fault tree analysis method, whereas the failure probability was simulated using a Weibull distribution. An inspection method based on crucial equipment's risk level was also added to the model (Elwerfalli et al., 2019). The proposed model improved equipment availability by 2% in addition to reducing maintenance-related costs. Al-Marri et al. (Al-Marri et al., 2020) presented factors to improve TAM implementation, reliability as well as efficiency. A focus group was used to identify the main factors (focus group), then an AHP was adopted to prioritize these factors. The main factors identified included labor skills, level of supervision, communication, safety, and on-site transportation.

Elwerfalli & Alsadaie (Elwerfalli and Alsadaie, 2020) presented a method for determining the optimal interval for a planned maintenance operation based on the risk level of equipment for a Gas-Liquid Recovery Unit. The risk estimation was computed using the API method, where failure rates were determined as a series arrangement of units with a Weibull reliability distribution function. The consequence of failure was defined based on environmental impact, production loss, and asset damage, which are evaluated using experts. A shutdown maintenance policy was optimized to attain good maintenance intervals. Keshavarz, Thodi, & Khan (Keshavarz et al., 2012) presented a risk-based assessment method to determine the implementation of turnaround (shutdown) maintenance. The failure probability and consequence of failure for different policy scenarios (shutdown period, standby, and

**Table 2**
Summary of articles that focused on turnaround maintenance.

| Application Subsector | Optimization Method | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|
| Refinery & Petrochemicals | Review of implementation methods | | Al-Turki et al. (2019) |
| Oil and gas industry | Software and company-specific systems | | Pokharel and Jiao (2008); Johansson and Rudberg (2010) |
| | Statistical analysis, probability | A: optimal result can be obtained D: not practical for a large number of equipment | Almomani and Aldaihani (2020) |
| | Statistics analysis, probability | | Elwerfalli, Khan, & Munive-Hernandez (2018; 2019) |
| | Focus group (with AHP) | A: expert opinion included D: company specific approach | Al-Marri et al. (2020) |
| Gas liquid recovery | Statistics analysis, probability (with API) | A: standardized method and can be applied to a large number D: optimal result not guaranteed | Elwerfalli and Alsadaie (2020) |
| Liquid natural gas plant | Statistics analysis, probability (with API) | | Keshavarz et al. (2012) |
| Natural Gas Plant | Lean management system implementation | A: an efficient and effective system can be achieved D: optimal result not guaranteed | Shou et al. (2021) |
| | Value-based classification | | Shou et al. (2019) |
| Gas processing and trucking | Data based analysis | [1]A: stakeholders are involved | Crestani et al. (2020) |
| Petrochemicals | Implemnetation Guideline | D: optimal result not guaranteed | Duffuaa and Daya, 2004 |
| | Qualitative data analysis | 1 . | Masubelele and Mnkadla (2021) |
| | Assessing company size and turnaround | | Halib et al. (2010) |

redundancy) were computed using equipment data (parameters). When an optimal risk level was reached, a shutdown decision was made to perform the maintenance activities on the facility. Shou et al. (Shou et al., 2021) presented a framework with a five-step procedure which included scope delineation, existing states definition (measurement), waste assessment, identifying improvement tools, and developing an implementation plan. Shou et al. (Shou et al., 2019) proposed a classification method for categorizing maintenance activities as value-adding or non-value-adding in order to implement lean operations. This classification was formulated using a value stream mapping method to evaluate the effectiveness and efficiency of a natural gas processing facility. The activities were defined from the perspectives of the manufacturing process, construction industry, and maintenance project field. Crestani, Le Dain, & Flaus (Crestani et al., 2020) constructed a decision support model for TAM scheduling under different constraints, processing environments, internal and external stakeholders' roles, and available data. The model assessed several components of the maintenance operation for gas processing plants and trucking (transportation) companies.

Duffuaa & Daya (Duffuaa and Daya, 2004) presented a general guideline that included steps for initiating, planning, executing, and terminating a TAM for the petrochemical industry. The specific activities in each step have been discussed in detail to give a complete implementation guide. Masubelele & Mnkadla (Masubelele and Mnkadla, 2021) surveyed stakeholders (managers, contractors, project team members) involved in the TAM operations from different industries (including the petrochemical) to identify the critical factors for implementing the policy. The factors, which included a commitment to the project, setting clear goals/objectives, clear definitions of roles/responsibilities, and the competency and experience of project managers, were prioritized using a mean score method. Halib, Ghazali, & Nordin (Halib et al., 2010) studied the impact of the organizational size of a company on the implementation of TAM. Based on multiple hypotheses, this study assessed the size of the company against the level of formalisation (a measure of administrative structure) and centralization (a measure of authority). The study showed TAM needed a high level of centralization and formalisation to meet operational schedules and requirements.

### 3.2.2. Risk-based maintenance

Risk-based maintenance (RBM) policy considers the risk associated with the failure of equipment emanating from different factors. These risks are not only used to determine the maintenance or inspection activities but also the optimization of the maintenance resources. Various critical analysis methods have been combined with this policy to enhance the optimization effort. The application of RBM approaches in the downstream petroleum industry has been summarized in Table 3. The policy combined various criticality assessment methods with different mathematical optimization models. The articles based on this approach have been briefly described below.

For the petrochemical and refinery plants, Hameed and Khan (2014) presented a procedure with three modules for the implementation of an RBM policy. The first module selected the equipment for maintenance from the risk evaluation process (derived from qualitative risk assessment based on production loss, damage, safety, and environmental impact). Failure data and consequences were estimated to analyze the risk level and determine the optimal maintenance interval. Bahoo-Toroody et al. (BahooToroody et al., 2019) proposed a risk-based procedure based on processing variables for the optimization of maintenance schedules. The first step was to adopt a model to address the fluctuation and uncertainty of acquired data. Failure probability was computed using a Dynamic Bayesian network and updating models using the probability of detection and sensors uncertainty. The last step (optimization) considered decision options (for scheduling the maintenance operation) and the costs of failure & maintenance.

A Bayesian network analysis method has also been used in the distribution section of the industry. Leoni et al. (Leoni et al., 2019) proposed a risk-based optimization method for scheduling maintenance. The method identified a component for which a fault tree analysis was prepared. The fault tree was mapped into a Bayesian network (backward analysis) that was used to determine failure rates which led to the estimation of the failure risk. Finally, the maintenance interval was determined for optimal operation. Singh and Markeset (2009) proposed a fuzzy logic framework for a risk-based inspection of pipelines for a processing plant. The proposed risk-based inspection model considered the operating conditions (temperature, flow rates, pressures, pH) and the inspection parameters (frequency, efficiency) to determine the estimated corrosion level in a pipe. From this estimation, the LOF and COF were computed to determine the risk level, ultimately optimizing the inspection schedule. The article proposed a fuzzy logic model to compute the trust level of the inspection results (based on the inspection's number, rate, and efficiency).

For the case of an ethylene oxide production facility, Hu et al. (2009) defined the RBM procedure into subsystem identification, risk

**Table 3**
Summary of articles that focused on the risk-based policy approach.

| Application Subsector | Optimization | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|
| Refinery & Petrochemical | Statistical analysis, probability (with risk matrix) | [1]A: standard and mathematical method. Specific factors can be studied. | Hameed and Khan (2014) |
| Natural Gas System | Statistical analysis, probability (with dynamic Bayesian) | D: no comparison among equipment | BahooToroody et al. (2019) |
| Natural Gas Regulating and Metering Station | Statistical analysis, probability (with Bayesian network) | | Leoni et al. (2019) |
| Pipelines Network | Fuzzy Framework | [2]A: uncertainty included D: complex computation | Singh and Markeset (2009) |
| Petrochemical | Statistics analysis, probability (with API) | 1 . | Hu et al. (2009) |
| | | | Khan and Haddara (2004) |
| | | | Luo et al. (2020) |
| | Fuzzy risk analysis methods | 2 . | F. Jaderi et al. (2019) |

estimation, risk evaluation, and maintenance steps. After identifying the subsystem, risks were estimated first by defining failure scenarios with their respective probabilities, then determining the failure consequence (failure and maintenance costs), and finally estimating the risk. The risk evaluation step defined the acceptable risk level before determining the maintenance plan that would be implemented for the subsystem. The plan involved different optimizing techniques, maximum failures under different preventive maintenance approaches (perfect or imperfect maintenance), and acceptable reliability levels. Khan & Haddara (Khan and Haddara, 2004) presented an RBM model that consisted of three interactive modules. The first module estimated risks by implementing four steps: failure scenario development, consequence assessment (considering fatality, economic, environmental, and system performance losses), failure probability analysis (using fault tree analysis (FTA) – cause of failure analysis through deductive method), and estimation. The second module evaluated the risk by formulating acceptable levels and comparing these levels to the estimated risks. Finally, the maintenance planning was performed by a cyclic estimation and optimization of the maintenance interval until good results were attained. Luo et al. (2020) presented a risk-based inspection and maintenance method for a large crude oil storage tank in the petrochemical industry. The method integrated a risk assessment (using the API method) with a periodic detection approach to optimize the maintenance operation. The proposed model was applied to maintain a storage tank floor failure due to corrosion. Maintenance policy optimization and component criticality analysis can be formulated using a fuzzy logic concept integrated with other mathematical methods. F. Jaderi et al. (2019) compared the risk-based method with fuzzy risk analysis methods for different components. For the criticality analysis (conventional RBM), a panel of experts defined the frequency of failure, parameters for the consequence of failure computation, criteria for criticality evaluation, and procedure for maintenance optimization. The experts determined the linguistic values for the same RBM criticality analysis steps and used fuzzy logic theories to compute the failure frequency, consequence of failure, and risk level. The method considered risk factors such as safety, environmental impact, production downtime, different types of costs, failure frequency, and mean time to repair.

### 3.2.3. Predictive maintenance

Adopting a predictive maintenance (PdM) policy requires a good data source for assessing the latest condition and the equipment's overall failure (reliability) characteristic to predict the maintenance requirement. Online monitoring of equipment and historical data are some of the data sources observed in the literature for this policy. Different methods have been utilized to exploit these data in order to provide an optimal predictive maintenance plan. Table 4 presents a summary of PdM applications in the downstream petroleum industries.

Helmiriawan and Al-Ars (2019) demonstrated a machine-learning approach for predicting equipment failures based on data of processing variables for an oil refinery plant. A recurrent neural network (RNN) was constructed to detect the slow changes in the deterioration of equipment performance and predict failures to help plan for maintenance operations. Pisacane et al. (2021) formulated a combined data-driven algorithm with a multi-objective optimization method to predict component failures for a refinery. The algorithm (heuristics) was used to extract the probability of failures fed to two optimizers: bi-objective mixed integer programming (using AUGMEnted CONstraint $\epsilon$ – AUGMECON) and bi-objective large neighborhood search. The AUGMECON obtained final results (an hour faster) even though there was no difference in the result's quality. Antomarioni et al. (2019) have proposed an integer programming approach to improve reliability under limited time and financial resource constraints. The method consisted of association rule mining (data mining tool) for predicting component breakage and an integer programming model to determine the optimal set of components to repair for an oil refinery plant. The association rules (developed using the plant's historical data) took 120–180 s for 10, 000–20,000 components. Al-Subaiei et al. (2021) proposed a smart PdM framework that continuously monitors and diagnoses equipment to provide information on the plant's availability and downtime for a refinery. The framework incorporated technical and financial feasibility studies. Zulkafli and Dan (2016) presented a PdM method using a probability distribution for a gasification processing unit. The method involved the computation of two parameters for the Weibull distribution (failure probability model). The failure probability was used to determine the maintenance operation frequency (the minimum and

**Table 4**
Summary of articles that focused on predictive maintenance optimization.

| Application Subsector | Optimization | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|
| Refinery | RNN | [1]A: data-based approach D: factor's details are hidden | Helmiriawan and Al-Ars (2019) |
| | Data-driven algorithm, multi-objective IP | | Pisacane et al. (2021) |
| | Smart maintenance framework | | Al-Subaiei et al. (2021) |
| | IP | [2]A: can attain optimal result D: less applicable for a large volume | Antomarioni et al. (2019) |
| Gasification processing unit | Weibull analysis method | | Zulkafli and Dan (2016) |
| Oil Pipeline, Pumps, Bearing | Review | | Jimenez et al. (Jimenez et al., 2020) |
| Pipeline | Stochastic, mathematical analysis | 1 . | Kermanshachi et al. (2020) |
| | Assessment matrix process (with FMSA) | | Nordal and El-Thalji (2021) |
| Petrochemical | IoT | 2 . | Bayoumi and McCaslin (2017) |

maximum maintenance activities) along with the amount of labor required for each activity.

Jimenez et al. (Jimenez et al., 2020) presented a survey on multiple PdM approaches for a pipeline distribution system. For a single model, the survey indicated that a knowledge-based, data-driven, or physical-based (using degradation laws) approach could be implemented, whereas the combination of these approaches led to multi-model methods. Furthermore, the policy implementation integrates methods for diagnosis and prognosis of equipment, providing information on the maintenance intervention time. Kermanshachi et al. (2020) developed a PdM model for pipeline corrosion failure to determine the optimal time interval with minimal maintenance cost for a natural gas transmission pipeline network. The failure rate was modeled using a probability distribution (stochastic), whereas mathematical analysis was applied to obtain the optimal cost and time for maintenance activities. The model's prediction accuracy was reported with $R^2$ greater than 0.8 for different cases. Nordal and El-Thalji (2021) proposed a PdM assessment matrix method (a heuristic procedure) to address the limitation of a failure mode and symptom analysis (FMSA) method, which was adopted to assess the reliability and risk associated with equipment. FMSA (introduced by International Organization for Standardization – ISO) is a method for criticality assessment that focuses on the symptoms of failure to monitor and prioritize the criticality of components or systems. The method was demonstrated in the maintenance of a centrifugal compressor (commonly used for transporting natural gas through the pipeline).

Bayoumi and McCaslin (2017) presented a tool for a petrochemical facility that integrated the different management levels for maintenance operations. This approach was based on the IoT, where information from various sources was collected to formulate a prediction model based on statistical analysis. The approach included data collection and integration, modeling, predicting, optimizing, acting, and presenting steps.

### 3.2.4. Condition-based maintenance

Condition-based maintenance (CBM) concentrates on the operational state of equipment for its service life. Periodic and non-periodic inspections can give the required information about the condition of a given asset. An in-service equipment condition monitoring system or indirect equipment deterioration method (like the number of run hours, the volume of processed product, and measured operating pressure or temperature) can also be used to determine the equipment's existing condition. The implementation of this maintenance policy is briefly discussed in this subsection. A summary of the articles covered is given in Table 5.

Reviews on the implementation of CBM (specific to the subsectors in the industry) have been identified in the literature. Abbasi et al. (2020) reviewed the implementation of a CBM policy for oil and gas rotating mechanical equipment (induction motors, compressors, and pumps). It categorized the different CBM approaches as model-based (utilizing mathematical model), knowledge-based (implementing data analysis algorithms), and parameter extraction-based (by means of equipment parameters estimation) methods. It analyzed the advantages, limitations, and practical application of each approach. Zhou et al. (2022) proposed a hierarchical coordinated reinforcement learning method that consisted of a hierarchical coordination mechanism and a distributed Q-learning method to optimize the maintenance operations. The article adopted a discrete event simulation method to compute the degradation rate, which was used to optimize large-scale maintenance problems.

Shin and Jun (2015) discussed the definition, benefits and limitations, international standards, techniques, and procedures for the CBM policy using case studies for a truck engine, lift arm of loader, locomotive, and compressor. Faris et al. (2019) presented a summary of maintenance system development and condition monitoring methods for gas compressor plants. The article discussed monitoring conditions (temperature, pressure, and gas properties), fault diagnosis, and implementation of the maintenance policy.

**Table 5:**
Summary of articles that focused on condition-based maintenance.

| Application Subsector | Optimization | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|
| Oil and gas Industry | Review | | Abbasi et al. (2020) |
| Natural gas plant | Hierarchical coordinated reinforcement learning | [1]A: data-based approach | Zhou et al. (2022) |
| Gas compressors, Locomotives & Trucks | Review | D: factor analyzed in detail | Shin and Jun (2015) |
| Gas compression plant | Maintenance operation overview | | Faris et al. (2019) |
| Petrochemical | Statistical analysis, probability | A: can analyze factors in detail D: less useful for a large volume | Kareem and Jewo (2015); Kareem et al. (2011) |
| | Convolutional NN | 1. | Shin et al. (2020) |

Kareem and Jewo (2015) adopted a method that used operational variables to measure critical equipment deterioration instantaneously, enabling organizations to predict failures and plan their maintenance activities accordingly. Three variables (temperature, vibration, and pressure) were measured for a centrifugal compressor to predict the failure rate in this approach. Mathematical analyses were used to determine failure rates and risk analysis using historical data for the equipment. In an earlier publication, Kareem et al. (2011) showed that this approach can reduce the cost of inspection (man-hour) by providing an optimum maintenance plan (cycle). Shin et al. (2020) presented a convolutional neural network (CNN) model for the CBM of pitting corrosion in the petrochemical industry. The model was formulated to detect low levels of corrosion. First, the CNN model was trained to detect the defect. Then a fitness evaluation method (fitness for service -API) was used to assess the damage. Depending on the result of the assessment, either a maintenance order (low-level damage) or further evaluation using a human operator (high-level damage) was recommended.

### 3.2.5. Reliability centered maintenance

The reliability of equipment can be computed by determining the failure or hazard rate obtained from the manufacturer or computed from historical data. The objective of this policy would be to keep the reliability level above a certain threshold. Table 6 presents a summary of the articles that demonstrate the application of this maintenance policy to the downstream petroleum industry.

Selvik et al. (2020) discussed the ISO standard (ISO 14,224:2016) on reliability and maintenance from the perspective of petroleum, petrochemical, and natural gas industries. The article compared the definition and concepts of reliability & maintenance with those concepts from other standards, such as ISO 31,000:2018 (uncertainty). These concepts are considered important in computing risk and implementing RCM operations. Focusing on the refineries, Deepak Prabhakar and D. (2013) presented a general overview of the implementation of the reliability-centered maintenance (RCM) policy. Conventional RCM consists of defining functions, failure modes, effects, consequences, management policies, and any proactive activities steps. Other versions of the policy included research-based RCM (mathematical or probabilistic approaches) and consultant-based RCM (streamlined RCM, PdM optimization, and total productive maintenance approaches). An accelerated RCM method comprised data collection, reliability analysis, failure identification, FMECA for critical equipment analysis, and implementation stages. The article described implementation models, requirements & limitations of the approach, and a few recommendations for all these methods. Cochran (Cochran, 2001) presented a Markov

**Table 6**
Summary of articles that focused on Reliability centered maintenance.

| Application Subsector | Optimization | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|
| Petroleum industry | ISO standards | | Selvik et al. (2020) |
| Refinery | Review of different methods | | Deepak Prabhakar and D. (2013) |
| | MDP | | Cochran (2001) |
| Transportation | Statistical analysis, probability | [1]A: can attain optimal result D: less applicable for a large volume | Mohammed et al. (2020) |
| Petrochemical | Intelligent system (with FMEA & FTA) | A: expert's input included. D: vary organizations-wise. | Li and Gao (2010) |
| | MTBF, MFOP, metrics comparison | 1. | Najari et al. (2018) |

model to determine the availability of a system (7 components). The model defined failure and repair rates as an exponential distribution for transition among the different states. The model considered 4 component states and 3 system states with only one maintenance policy (action).

Mohammed et al. (2020) proposed an RCM policy to improve the reliability of loading/unloading equipment. The model developed identified the critical components along with their failure modes. The failure rate and mean time between failures of components (modeled as exponential distribution) determined the system's reliability, which was ultimately used to schedule the optimal maintenance period. For a case from the petrochemical industry, Li and Gao (2010) applied a reliability-centered intelligent maintenance system that combined radical maintenance policy (RM - a policy focusing on the root causes of failure) based on FMECA and FTA to identify the root causes of failures. The system constitutes data collection, subsystem identification and evaluation, criticality assessment, failure mode analysis, and maintenance policy formulation steps. Najari et al. (2018) compared two reliability metrics: maintenance-free operating period (MFOP) and mean time between failure (MTBF). MTBF is defined as the average time length between failures (the ratio between the total number of failures and total time horizon), while MFOP is defined as the period over which a system performed the expected operation. MTBF demonstrated inherent disadvantages by accepting failures and unscheduled maintenance in the computation, whereas MFOP focuses on the operational period.

### 3.2.6. Mixed maintenance policies

Some of the maintenance policies have been combined to best fit the requirements of different types of equipment. Table 7 presents the summary of these approaches. The mixed maintenance policies combined CM primarily with one or more PM policies. Some of these methods incorporated criticality assessment methods discussed in the previous section.

For the petroleum industry, Aghaee et al. (Aghaee et al., 2020) applied different maintenance policies along with a fuzzy Delphi-based method to evaluate priorities and a fuzzy decision-making trial evaluation and laboratory (DEMATEL) method to determine the relationship among the assessment criteria. Analytical Network Process (ANP), a more general form of AHP, was used to compare and select the best maintenance for each priority level. Elhdad, Chilamkurti, & Torabi (Elhdad et al., 2013) presented an ontology and business process-based framework (on PM and CM policies) to monitor and maintain a petroleum processing plant. The Framework defined different functions in the production process (including their inter-relationship) to monitor the performance of devices in addition to initiating maintenance operations based on the device's instant states.

Tan et al. (Tan et al., 2011) adopted the API risk-based approach to

**Table 7**
Summary of the articles that focused on a mixed maintenance policies approach.

| Application Subsector | Policies Combined | Optimization | Advantage (A) Disadvantage (D) | Publication |
|---|---|---|---|---|
| Petroleum industry | CM, PM, CBM, RCM, and PdM | Fuzzy logic, statistical analysis, matrix (with Fuzzy AHP) | [1]A: uncertainty included | Aghaee et al. (2020) |
| | CM and PM | Ontology and business process-based framework | D: complex computation | Elhdad, Chilamkurti, & Torabi (2013) |
| Refinery & Petrochemical | CM, CBM, RCM, and PdM | Statistics analysis, probability, Matrix (with API & AHP) | [2]A: comparison steps included | Tan et al. (2011) |
| | CM and PM | Maintenance performance indicators and management | D:- vary organization-wise. | Sailer & Hladík (2021) |
| Refinery | CM and PM | Associative rules | | Antomarioni et al. (2018) |
| | CM and PM | Monte Carlo, GA (with FEMA) | A: suitable for large volume | Bagajewicz (2013) |
| | PM, PdM, TAM | Implementation guidelines | D: factor's details are hidden | Kosta & Kosta (2013) |
| | Criticality, identification of equipment | Review of incidents | | Nelson & Anderson (2021) |
| Gas industry | Fault diagnosis, RBM | Review | | Faris, Elamin Elhussein, & Yousif (2019) |
| Oil transfer station | RBM and CBM | IoT | A: data-based approach D: factor's details are hidden | Wang & Gao (2012) |
| Pipeline network | CM and PM | Markov Decision Process | A: uncertainty was included D: optimal result not guaranteed | Bediako et al. (2020) |
| Petrochemical | Opportunistic with CM or PM | Monte Carlo simulation | | Laggoune, Chateauneuf, & Aissani (2009) |
| | CM, PM, CBM, RCM, PdM | Fuzzy distance-based analysis method (Fuzzy AHP) | 1 . | Panchal et al. (2017) |
| | CBM, CM, Opportunistic | Multi-objective optimization (GA) | A: suitable for large volume D: optimal result not guaranteed | Alrabghi, Tiwari, & Savill (2017) |
| | RBM and CBM | Decision-making System | | Yuan, Wang, & Gao (2012) |
| | CM, PM | Wiener degradation, Bayesian inference | A: factor analysis included D: complex formulation | Zhao et al. (2021) |
| | CBM, Scheduled, Proactive, and Design-out Modification | AHP | 2 . | Elijaha (2021) |
| | CBM, PDM, RBM, and TPM | Formulating, planning, implementation Initiate, plan, execute | | Velmurugan & Dhingra (2015); |

classify equipment's criticality and proposed a maintenance policy for each category that was selected using AHP. Various maintenance policies were evaluated for each category, and then the appropriate policy was established for the respective asset. Accordingly, CM policy was set for the lower-risk category, whereas PM policies, such as RCM, were implemented for high-risk (critical) assets. Sailer & Hladík (Sailer and Hladík, 2021) presented a maintenance management model to improve the efficiency of maintenance organizations by identifying key performance indicators, organizational structure, and asset management processes. The model described different components of the maintenance management system, which include planning, scheduling, analysis, execution, improvement, measurement, and requirements of maintenance operations. Antomarioni et al. (Antomarioni et al., 2018) applied a data mining tool (association rules) where past data about the stoppages or component breakdowns over a given period was used to provide information about optimal maintenance policies decision (implement predictive or correction interventions). Bagajewicz (Bagajewicz, 2013) described Monte Carlo and GA simulation methods for the optimization of different maintenance objectives (profit, cost, and safety) subjected to various constraints (labor, budget, and acquisition & inventory of spare parts). Monte Carlo simulation was used to optimize simple maintenance problems by randomly sampling the model variables, whereas the GA was used to solve complex problems. The proposed model reported the number of resources (for example, labor) to attain the optimal objective (economic loss). Kosta & Kosta (Kosta and Kosta, 2013) presented a complete guide on the implementation of maintenance operations in a refinery. This research classified the main maintenance operations in a refinery as mechanical, electrical, instrumentation, and civil functions. It proposed various approaches for groups of equipment (structure or facility) inspection, failure analysis, and the optimization of the adopted policy (CM, PM, PdM, and TAM). Nelson & Anderson (Nelson and Anderson, 2021) proposed a guide for identifying, documenting, inspecting, planning, and resolving critical equipment failure causes. The guide adopted different standards (API, Industrial Valves, American Society of Mechanical Engineers) for identifying assets to include in the list. The article discussed the adoption of criticality assessment methods (FTA, FMEA, Layer of Protection) to determine risk levels. It emphasized the importance of paying more attention to minor (mostly overlooked) equipment, which could cause accidents in the industry.

Focusing on the distribution section of the industry, Faris, Elamin Elhussein, & Yousif (Faris et al., 2019) presented a review of several approaches for condition monitoring, fault diagnosis, reliability/availability/maintainability analysis, and risk-based inspection for compressors. The study discussed failure probability assessment approaches, risk estimation methods, operating parameters evaluation, and maintenance policy optimization techniques for the equipment. Wang & Gao (Wang and Gao, 2012) proposed a risk- and condition-based indicator decision-making system (RCBIDS) using IoT for an oil transfer station. The system was comprised of different operational activities, including fault or defects detection, remote condition monitoring, maintenance technical support service, and maintenance decision support system. Bediako et al. (Bediako et al., 2020) proposed a Markov Decision Process (MDP) model for optimizing the maintenance of pipelines under CM and PdM policies for a cost-minimizing objective. The deterioration rate was determined using periodic and continuous inspection. The model defined maintenance actions (preventive or corrective), states (based on the deterioration) of the pipeline, and transition probability between the states.

Laggoune, Chateauneuf, & Aissani (Laggoune et al., 2009) proposed an optimization model based on a PM policy for a petrochemical plant with multiple component systems (series arrangement). An opportunistic maintenance policy was incorporated into the model to utilize the shutdown period. The components' failure probability (time to failure) was determined using historical data. The model's objective was to reduce the maintenance cost for components in a series system with a random failure. A Monte Carlo simulation was used to show that the model can reduce up to 70% of the maintenance cost. Panchal et al. (Panchal et al., 2017) formulated a fuzzy AHP approach with a combinative distance-based assessment model to identify the criticality of components and proposed the optimal maintenance policy (combination of CM, PM, CBM, RCM, and PdM). Alrabghi, Tiwari, & Savill (Alrabghi et al., 2017) applied a Genetic Algorithm (GA - GAnetXL) to optimize two objectives (minimize maintenance cost and maximize production throughput). A simulation-based approach modeled the industrial environment, while the GA optimized the policies (CBM, CM, and Opportunistic Maintenance) for different types of equipment. Yuan, Wang, & Gao (Yuan et al., 2012) proposed a maintenance decision-making system architecture where reliability-centered maintenance, condition monitoring system (assessment and prediction), and manufacturing execution system were integrated. A real-time database was used to provide a unified data structure to implement man-machine interfaces. The system determined maintenance priorities, risk levels, degradation trends, and optimization of maintenance activities. Zhao et al. (Zhao et al., 2021) presented a maintenance policy optimization approach to address the uncertain nature of degradation. Bayesian analysis was used to dynamically update the degradation parameters, formulated as a Wiener probability distribution. Different parameters were used to formulate the probability distribution of varying asset degradation models. For a short-time planning horizon, PM or CM policies were carried out to minimize the expected cost of maintenance. Elijaha (Elijaha, 2021) compared the effectiveness of four maintenance policies (CBM, Scheduled, Proactive, and Design-out Modification) for a pump. The model incorporated defining subsystems, collecting data, failure analysis, FMEA, criticality analysis, policy selection using AHP, determining maintenance action, implementation, and evaluation steps. The article demonstrated the implementation of the selected policies for the components of a pump. Velmurugan & Dhingra (Velmurugan and Dhingra, 2015) proposed a conceptual framework for implementing different maintenance policies by reviewing various maintenance-related publications from the literature. The framework consisted of processes for formulating, planning, implementing maintenance policies, and assessing maintenance performance. The article also reviewed the tactical aspects of a few maintenance policies (CBM, PdM, RBM, and TPM).

### 3.3. Others

Other maintenance objectives have also been optimized using various methods in the downstream petroleum industries. These objectives can be directly related to the implementation of maintenance operations (such as scheduling, operations proficiency, and mechanization) or the integration of other related organizational functions (safety, production, and inventory) to increase the effectiveness of maintenance operations (Table 8).

#### 3.3.1. Planning and scheduling

Maintenance operation planning & scheduling are vital in the downstream petroleum industry. Various optimization methods have been proposed to model and solve these functions. Seif et al. (Seif et al., 2021) developed a mixed-integer optimization model for maintenance scheduling problems in oil and gas processing plants. The model consisted of multiple maintenance campaigns that considered many components and labor. The objective of the optimization was to reduce the shutdown cost of maintenance. Constraints included the time boundaries for each campaign, available resources, workload balance, and shutdown indicators. Alkhamis & Yellen (Alkhamis and Yellen, 1995) adopted an integer programming model for a maintenance scheduling optimization problem. The model maximized the unit/equipment utilization under PM-related constraints (such as maintenance window, resource, logic, operation sequence, and maintenance completion). Hou et al. (Hou et al., 2022) proposed a short-term production scheduling

**Table 8**
Summary of articles that focused on maintenance optimization.

| Study focus | Application Subsector | Optimization | Advantage (A) Disadvantage(D) | Publication |
|---|---|---|---|---|
| Planning and scheduling | Oil and Gas plant | Mixed Integer Programming | [1]A: optimal results can be obtained D: not practical for a large volume of equipment | Seif et al. (2021) |
| | Refinery | Integer Programming | | Alkhamis & Yellen (1995) |
| | | Mathematical model | | Hou et al. (2022) |
| | | Mixed-integer NLP | | Xingchun, Sujing, & Qiang (2022) |
| | | Mathematical analysis | | Yabrudy Mercado et al. (2020) |
| | Gas processing | Nonlinear optimization problem | [2]A: suitable for a large volume D: optimal results not guaranteed | Ahmed et al. (2015) |
| | Liquefied Natural Gas (LNG) | Genetic Algorithm and simulation | | Hameed et al. (2019) |
| | Gas distribution | Statistical analysis, probability | [3]A: can analyze factors in detail D: less useful for a large volume | Carlucci & Tognarelli (2015) |
| | | Linear programming | 1. | Gargari, Hagh, & Zadeh (2021) |
| | Hydrocarbon Supply chain | Mixed Integer Programming | | Ghaithan (2020) |
| | Petrochemicals | Statistical analysis, probability | 3. | Berk & Moinzadeh (2000) |
| Inspection interval | Refinery | Monte Carlo simulation | [4]A: provide a good estimation D: optimal result not guaranteed | Mendes (and. L. M. W. Mendes, 2018) |
| | | Expectation theory | | Abbasinejad, Hourfar, & Elkamel (2021) |
| | Pipelines | Management guide | | Amani (2022) |
| Safety | Refinery | Markov Decision Process | [5]A: models uncertainity D: less useful for large volume | Redutskiy (2017) |
| | | Combined fuzzy NN, firefly heuristics | 2. | Zhao et al. (2020) |
| Evaluation | Petrochemical | Performance metrics; Economic, environmental, social evaluation | | Assaf et al. (2015); Tong et al. (2020) |
| | | Supplier evaluation using TOPSIS | | Tong, Pu & Ma (2019) |
| | | Evaluation using questionnaires | | de Vries & Visser (2021) |
| Integrated maintenance | Refinery | Monte Carlo simulation | [4]. | Tsutsui & Takata (2010) |
| Assessing outsourcing | Refinery | System dynamics model | 2. | Kaveh Pishghadam & Esmaeeli (2021) |
| Operation proficiency improvement | Gas metering stations | Integer programming and heuristic | 1. | Cassettari, Gaggero, & Saccaro (2021) |
| Maintenance location optimization | Gas distribution network | Mixed-integer programming using GAMS, Cplex | | Malec, Benalcazar, & Kaszyński (2020) |
| Procedural maintenance approach | Gas distribution network | Non-Markovian stochastic Petri nets | 5. | Carnevali et al. (2014) |
| Failure mode determination | Petrochemical | FMEA; Fuzzy logic | A: models uncertainity D: complex model formulation | Azadeh, Ebrahimipour, & Bavar (2010) |
| Integrating mechanization | Petrochemical | | | Yin et al. (2020); Shan et al. (2020) |

model for the maintenance of charging tanks to ensure a continuous process flow. A multi-objective model with constraints such as material conservation, resource capacity, assignment, and processing limitations was considered in the model. An adaptive enhanced selection pressure algorithm (GA-based metaheuristics) was used to solve the problem. Xingchun, Sujing, & Qiang (Xingchun et al., 2022) presented a simultaneous production and maintenance scheduling model for a refinery. The model formulated a multiobjective mixed-integer nonlinear programming method to minimize operating costs and total risk arising from maintenance activities. The constraints consisted of resource & processing limits, maintenance logic, risk level evaluation, and budget restriction. Yabrudy Mercado et al. (D. F. C. J. S. L. B. and. C. A. C. Yabrudy Mercado 2020) presented an efficiency-centered maintenance method (from an energy conservation and cost reduction perspective) to develop a maintenance plan for a heat exchanger cleaning operation. The approach aimed at determining a schedule and type of activities for proficient maintenance service based on criticality analysis of different equipment's condition indicators. Its implementation saved up to US$ 150,000 on maintenance costs.

Ahmed et al. (Ahmed et al., 2015) proposed a goal programming model for optimizing a nonlinear problem with multiple maintenance objectives (maintenance cost, reliability, and equipment availability) for a gas processing facility. Each objective (for a specified time horizon) has its respective constraints and lower bounds extending over a range of equipment in the problem formulation. For example, reliability depended on the failure rate probability (distribution) selected, whereas cost was subjected to the number & type of maintenance of operations. The model incorporated CM and PM, replacement, and inspection operations with various outcomes depending on the equipment's service life and reliability level threshold. Hameed et al. (Hameed et al., 2019) developed a decision support tool for two-objective optimization problems in RBM scheduling. The tool developed combined a genetic algorithm (GA) and simulation-based optimization methods with objectives to minimize the total cost of maintenance and improve reliability. Constraints incorporated functions for determining the effective age of the equipment, preventing activity overlaps, as well as implementing maintenance operations. The proposed tool was demonstrated on a Liquefied Natural Gas (LNG) plant.

Carlucci & Tognarelli (Carlucci and Tognarelli, 2015) presented a maintenance schedule optimization model for a gas generator under different working environments and failure probability distribution. The article showed how the generator was affected by the available stations, the maintenance operations, and the spare parts inventory. The model employed reliability software (BlockSim) as an optimization tool. Gargari, Hagh, & Zadeh (Gargari et al., 2021) formulated a PM schedule for a multi-energy gride (combining electric and natural gas supply) to enhance the supply system's resilience. The schedule adopted a sequential approach which included data collection, selecting operational scenarios, performing operations, integrating maintenance, creating a schedule, optimizing resiliency, and repeating the process until the best scenario was attained. Ghaithan (Ghaithan, 2020) presented a mathematical model for maintenance planning and scheduling in the hydrocarbon supply chain network. The approach considered the processing operation as part of the modeling. A mixed-integer programming method was applied to maximize profit subject to various constraints (demand and supply balance, processing capacity, production and maintenance time span, resource limitations, and so on).

Finally, considering cases from the petrochemical industry, Berk & Moinzadeh (Berk and Moinzadeh, 2000) formulated a maintenance scheduling model for *n* identical machines from different industrial sectors. It considered limited resources and identical & independently distributed maintenance time to assess the profit generated based on two variables, i.e., the number of machines operating and their ages. Operating characteristics curves were used to compare the profit rates for different scenarios.

### 3.3.2. Inspection interval determination

Inspection intervals impact the equipment's reliability and maintenance cost differently. Therefore, inspections would have to be optimized for the best outcome of these maintenance parameters. Mendes (Mendes, 2018) presented a Monte Carlo simulation method for determining the inspection period for a pump used in refineries. A Weibull probability distribution was proposed for a cold standby system to formulate the failure time. Costs related to inspection operations were minimized in the method. Abbasinejad, Hourfar, & Elkamel (Abbasinejad et al., 2021) developed a model for estimating the interval of a proactive maintenance policy based on expected utility theory (expected future use of equipment). The research aimed at providing a maintenance plan with the lowest cost and acceptable reliability, availability, and safety. The model first determined failure probability (parameters for Weibull distribution), then calculated monetary parameters, and finally computed the optimum maintenance interval. Amani (Amani, 2022) reported a framework to improve the effectiveness and efficiency of a pipeline inspection management system. The framework consisted of developing the information (identifying the pipeline, measuring defects, assessing, designing the inspection method, performing the inspection and reporting), creating an integrated model, and validating steps. The framework was built on questionnaires conducted in the industry.

### 3.3.3. Safety

Safety issues are crucial for all operations in the downstream petroleum industry since most of the products processed pose a range of accidents and hazards to human life as well as the environment. Maintenance operations are studied in the industry from the perspective of mitigating the dangers that arise from faulty processing equipment in addition to the risk caused by maintenance operations. Redutskiy (Redutskiy, 2017) proposed a black-box approach for various failures and incidents with the associated restoration and maintenance operations. The approach considered minimizing the probability of failure, downtime, and cost as an objective and built a system-level Markov process model with various states along with the respective action. Zhao et al. (Zhao et al., 2020) presented fuzzy-based neural network (NN) approaches to evaluate the risk level (using indices) of maintenance operations for a refinery unit. The main goal of the evaluation was to ensure the safety of the operations. It was performed based on factors such as the operating environment, maintenance technician & materials, management, and the specific type of operations. The approach formulated a fuzzy-based NN model and used a firefly algorithm as a solver.

### 3.3.4. Maintenance operation evaluation

A few publications have presented methods for evaluating maintenance operations. Assaf et al. (Assaf et al., 2015) and Tong et al. (Tong et al., 2020) presented maintenance efficiency measurement methods. The former publication adopted a data envelopment analysis method for five key performance metrics (reliability, cost, time, non-ordinary task, and labor) to analyze the maintenance. A software (Efficiency Measurement System) was used to assess maintenance units. The latter publication proposed a framework for performance evaluation criteria for maintenance services. It implemented a fuzzy PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) method based on three evaluation criteria categories: economic (cost, service reliability), environmental (eco-design, resource consumption, recycling), and social (stakeholders, employee, safety). Tong, Pu & Ma (Tong et al., 2019) presented a methodology for selecting and evaluating equipment maintenance service providers with a case study from the petrochemical industry. The proposed methodology evaluated service providers from a safe and sustainable production perspective using the fuzzy TOPSIS method. The criteria included market acceptance, equipment and resource condition, and safe production. de Vries & Visser (de Vries and Visser, 2021) proposed several critical factors for evaluating the performance of a maintenance team in the petrochemical industry. These factors assessed maintenance operations (identification, planning, scheduling, and execution), equipment effectiveness, cost, safety, environment, human factor, and organizational issues. The evaluation was conducted based on the responses from questionnaires.

### 3.3.5. Miscellaneous topics

Other maintenance objectives found in the literature have been briefly discussed below.

- *Refineries*: Tsutsui & Takata (Tsutsui and Takata, 2010) presented a Monte Carlo simulation system that combined maintenance and production operations optimization to reduce the loss due to machine failure and downtime. The losses considered included inspection cost, repair cost, and operator's injury for a desulfurization facility in a refinery. The system incorporated the production operations, planning (processing & maintenance), failure likelihood assessments, condition monitoring, and inspection components. Kaveh Pishghadam & Esmaeeli (Kaveh Pishghadam and Esmaeeli, 2021) designed a model to analyze outsourced maintenance services in terms of their effectiveness, efficiency, and profitability for refineries. A system dynamics model with different scenarios was used to analyze the variables that affect the system to obtain the optimal service.
- *Gas distribution*: Cassettari, Gaggero, & Saccaro (Cassettari et al., 2021) formulated an optimization model for a four objectives problem (reduce the number of operators, reduce idle time, reduce the distance traveled, and balance operators' workload) for gas metering maintenance service. The problem was formulated as a vehicle routing problem. An Integer programming (for small-size problems) and a heuristic (for large-size problems) were proposed to solve the problem. The constraints included the number and type of activities, time horizon, number of operators, precedence relationship, distance, and travel time. The heuristics comprised clustering, cluster optimization & merging, and refinement steps. Malec, Benalcazar, & Kaszyński (Malec et al., 2020) presented an optimization model for determining maintenance centers' locations for a gas distribution network. The objective of the model was to minimize the maintenance cost while improving the maintenance service and response time for the network. The problem, formulated as a mixed-integer programming model, was solved using commercial software (GAMS and CPLEX). Constraints included resource capacity limitation, assignment restriction, and operational flow after the respective maintenance services. Carnevali et al. (Carnevali et al., 2014) proposed a maintenance procedure with multiple implementation phases based on the gas distribution network's physical and geographical parameters. The procedure adopted a non-markovian variant of stochastic Petri nets to obtain information

on the availability of the network sections and overall service quality. It incorporated a quasi-static fluid-dynamics analysis and failure & consequence management procedures (including time-dependent parameters).

- *Petrochemical*: Azadeh, Ebrahimipour, & Bavar (Azadeh et al., 2010) proposed a fuzzy rule-based inference system that mimics human reasoning through interactive knowledge acquisition to pinpoint the failure cause of a pump based on operating parameters. These parameters included flow rate, pressure, temperature, vibration, and brake horsepower. The rules were developed by integrating maintenance knowledge (from a handbook and experience) with the FMEA method (from the operating parameters). Yin et al. (Yin et al., 2020) and Shan et al. (Shan et al., 2020) proposed different mechanization technologies for maintenance operations after assessing existing technology in petrochemical industry facilities. Mechanization is the transformation of manual (human or animal-powered) operations to complete machine-based operations. This transformation's main objective was to improve maintenance operations' productivity. Yin et al. (Yin et al., 2020) assessed the existing mechanization level to propose appropriate technologies for implementation. The article identified seven levels of mechanization: complete manual, static hand tools, flexible hand tools, automated hand tools, static machine (workstation), flexible machine, and completely automated. Shan et al. (Shan et al., 2020) proposed a mechanization level assessment method (petrochemical maintenance mechanization assessment - PEMMA) to facilitate the mechanization process. The method followed defining the mechanization scale, identifying major activities and the required equipment, developing scoring schemes, determining an assessment index, and validating steps.

## 4. Discussion

The maintenance optimization approach selection varied depending on the size of the asset considered in a given campaign. The optimization problem for a single piece of equipment focused on determining the optimal objective value which is affected by various parameters and variables related to the equipment. The objective included minimizing cost, improving reliability/availability, or reducing risk levels, while the constraints take in equipment failure rate, inspection frequency, acceptable risk level, and different maintenance-related costs. On the other hand, when a collection of equipment or machinery was considered (usually at the plant level), prioritization (criticality) tools were added to the optimization model. These tools enabled companies to arrange maintenance operations in one or multiple facilities in an organization.

The distribution of the reviewed articles has been analyzed to better understand the maintenance implementation trends in the downstream petroleum industry. Fig. 3 shows the reviewed articles' distribution in the industrial subsector. The processing sector of the industry (the refineries and natural gas processing) has received more attention than other sections, while the transportation sector has received the least attention, with the petrochemical & distribution network laying between these two extremes.

Fig. 4 shows the distribution of criticality analysis methods in the reviewed articles. API and AHP were the most common analysis methods employed for this method, whereas FMEA, combined analysis methods (merging methods like API, AHP, FMEA, fuzzy logic, and heuristics), and other methods (machine learning, TOPSIS, Robust portfolio model, Pareto analysis, Bayesian analysis, and self-organizing map) were observed in the review. Figs. 5 and 6 present the composition of the maintenance policy type and the optimization method adopted by the articles. As shown, the TAM, RBM, and PdM policy approaches were the most frequently implemented maintenance policies, whereas exact methods based on probability, statistics, matrix, and mathematical programming (such as linear, integer, nonlinear and stochastic) dominated the methods.

Fig. 7 show the number of publications on criticality analysis methods (prior to 2010, 2010 - 2015, and post-2015). API was the industry's most common criticality analysis method before 2010. However, the use of this approach has declined, while the implementation of AHP and newer methods have grown significantly over the years. Combined analysis has remained a moderately popular method, whereas FMEA/FMSA slightly declined in their applications. This decline can be partly attributed to the recent evolution of the FMEA method. The development of new criticality analysis methods has sharply increased over the last era. These methods addressed diverse requirements for prioritizing maintenance operations in the industry.

Based on the analysis given in Fig. 8, the implementation of most policies has increased over the past few years. The most radical increase observed was in the implementation of PdM, coinciding with the popularity of tools like machine learning and data mining that are frequently applied with this policy. TAM has remained the most popular policy in the industry, whereas RBM, CBM, and RCM policies have continued to grow in implementation. Combined policy approaches have grown significantly, which in most cases, are mainly used to supplement CM with different PM policies. Maintenance-related topics in the downstream petrochemical industries have grown considerably especially in the post-2015 era. As the knowledge base and impact of maintenance function increased, research has expanded to enhance the operations' proficiency and efficacy. Overall, the diversity of policies and criticality analysis methods has increased over the past decade with new methods, either developed or adapted to the needs of the industry.

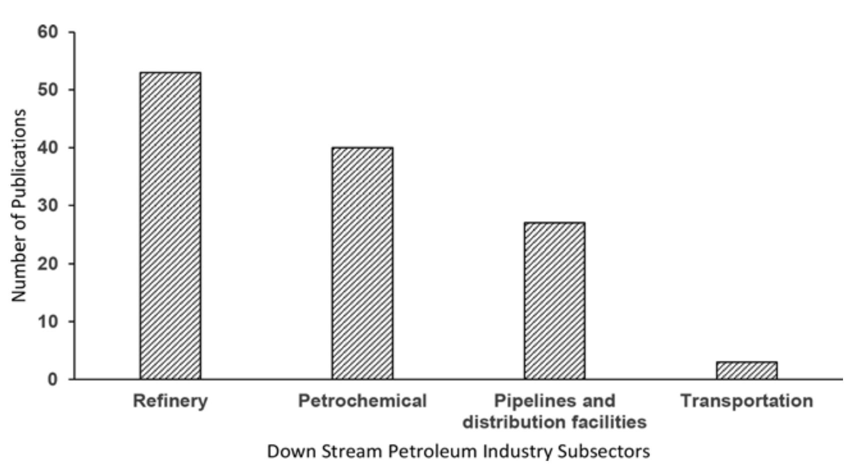


**Fig. 3.** Industrial sector-based distribution of the reviewed articles.

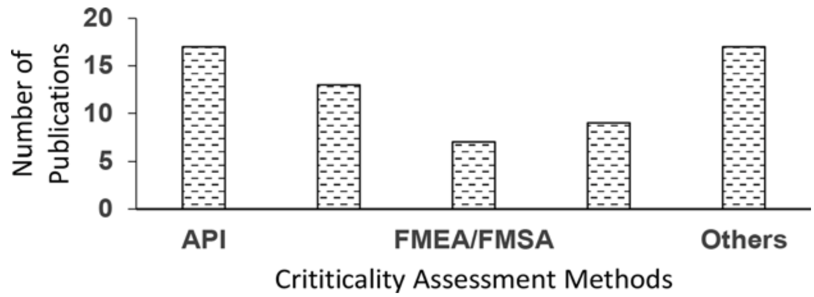


**Fig. 4.** Criticality determination approaches.

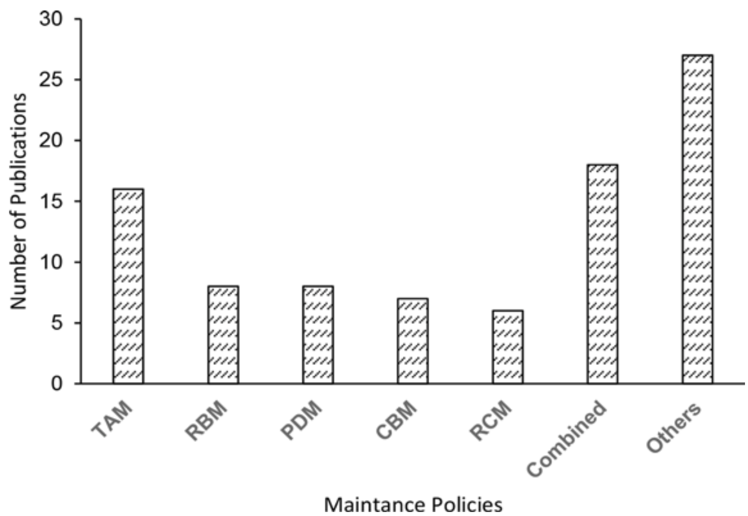


**Fig. 5.** Maintenance policy-based distribution of the reviewed articles.

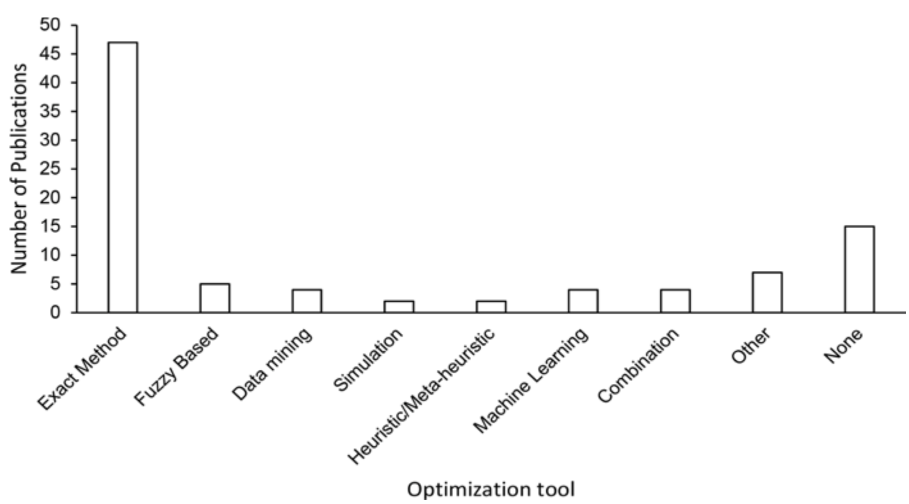


**Fig. 6.** Maintenance optimization approaches.

## 5. Future research direction

The downstream petroleum industry covers a wide range of processing and distribution facilities with complex procedures and equipment. As a result, the maintenance optimization requirements of facilities in the industry are highly diverse. Studies on the optimization methods identified in the literature have been discussed in Section 3. This section presents potential research extensions to these studies that could impact optimization approaches in the industry.

Crude petroleum and its by-product processing have been identified as the industry's main focus area for maintenance optimization research. Even with such research inclination, the optimization studies can be extended in all categories. Potential optimization and criticality analysis methods can be explored by benchmarking practices in related industries. For example, policy optimization can consider the extension of RBM and CBM policies as well as the implementation of new (least common) policies, such as time-based and opportunistic maintenance policies (Chin et al., 2020). Criticality analysis methods such as crisis tree analysis, adaptive risk analysis, process graph, and event tree can be investigated for potential industry applications (Chin et al., 2020).

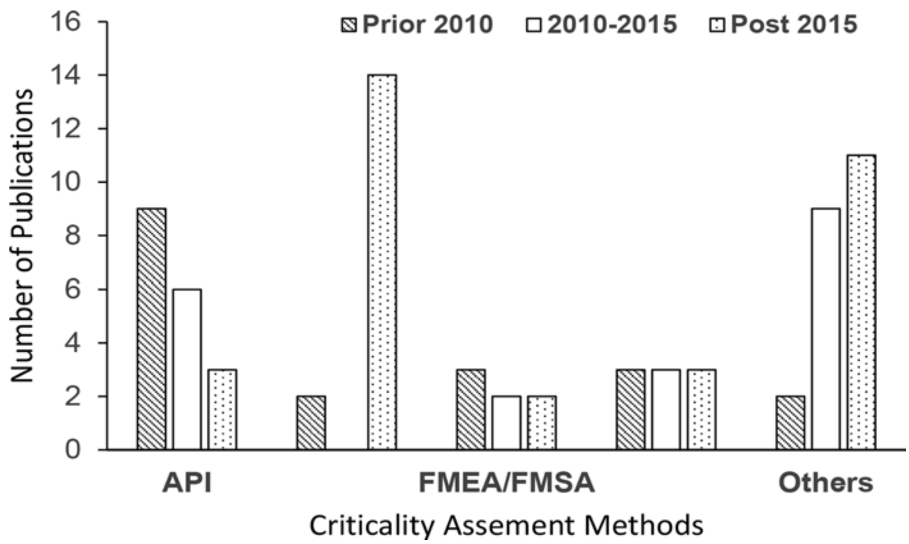


**Fig. 7.** Yearly distribution of criticality analysis methods.

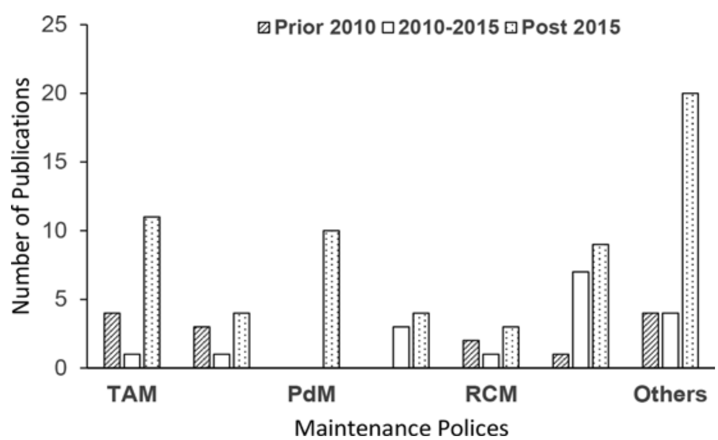


**Fig. 8.** Yearly distribution of maintenance policy.

Maintenance features such as condition monitoring, inspection, replacement, repair, and dependency for single and multi-component systems can be studied to enhance the optimization model (De Jonge and Scarf, 2020; Keizer et al., 2017). As most industrial processes possess stochastic attributes, integrating stochastic optimization methods could lead to a more realistic problem formulation (Alaswad and Xiang, 2017). These stochastic formulations can define deterioration rates, reliability, failure risk, available resources, and other maintenance-related factors. The combination of maintenance with different organizational functions (inventory and production management) can be another research extension (Hwang and Samat, 2019; Van Horenbeek et al., 2013). This approach can enhance the impact of the maintenance optimization model by providing organization-wide solutions. Sustainable maintenance can also be addressed in more detail, even though few articles have already begun studying the topic (Saihi et al., 2022; Olugu et al., 2022; Hosseinzadeh et al., 2023).

The maintenance of distribution facilities for semi-processed and finished products provides a good research prospect in the industry. In addition to some of the research extensions that these facilities share with processing sections, the combined safety and maintenance optimization problem could be valuable to the knowledge base. These facilities also extend over large regions, requiring the integration of logistics when formulating the optimization problem. The maintenance of a fleet of trucks or trains to transport products can be another future research direction. As shown in Section 4, the research in this direction is minimal despite its importance to the industry. Some topics that could be considered include maintenance cost optimization methods based on travel distance and road conditions, focusing on critical components (Zhetesova et al., 2020). Vujanović, Momčilović, & Medar (Vujanović et al., 2018), Durán et al. (Durán et al., 2021), Kfita & Drissi-Kaitouni (Kfita and Drissi-Kaitouni, 2017), and Wang et al. (Wang et al., 2021) have discussed other directions for this research prospect.

## 6. Conclusion

Maintenance is an essential function that draws research in the downstream petroleum industries. These research varied in terms of asset prioritization, applied policies, optimization methods, management framework/guidelines, implementation control, and evaluation to tackle the diverse maintenance needs of the subsectors. The overall approach observed was to arrange first components/equipment based on their criticality to the production process, safety, environment, and/or failure rates, and then either perform the maintenance operations or select an appropriate maintenance policy to optimize objectives such as maintenance cost (summation of maintenance-related cost), reliability, and availability. Criticality analysis methods such as the API approach, AHP, and FMEA were prevalent with various development of these methods and new ones. When a large volume of assets is considered for a maintenance campaign, optimizing policies may not be a practical approach to implement. Therefore, the criticality analysis methods were adopted as the sole optimization tool.

Though dominant policies were frequently applied in the industry (like TAM and different mixed approaches), a range of policies (including RMB, PdM, CBM, and RCM) have also been implemented independently. When considering single equipment or machinery, the optimization addressed model variables or maintenance policies that attain the optimal value for the objective set. As an optimization tool, exact methods have been widely used, but other methods such as fuzzy logic, heuristics, machine learning tools, and different combined methods have also been observed in the publications. Optimization also included other focus points, such as maintenance operation scheduling, safety (both the maintenance operation and the overall safety of the production process), supplier selection, outsourcing, joint production-maintenance approach, and maintenance mechanization. Furthermore, several articles have demonstrated the different maintenance implementation frameworks and evaluation methods.

Maintenance optimization approaches have grown in terms of the sub-sectoral coverage, range of policies implemented, variety of critical analysis methods, and diversity of optimization tools adopted over the years in the industry. However, due to the vast number of industrial facilities, research should be expanded to reach every corner of the industry. Researchers can explore the implementation of potential critical assessment methods and policies, stochastic methods, and industry-specific research gaps (sub-sectoral or aggregated supply chains). Integrated maintenance function over the supply chain can result in more lean, cost-effective, and efficient operations.

To sum up, maintenance functions in the downstream petroleum industry entail a large number of complex activities bounded by time and cost. It directly affects the production process's profitability, safety, and environmental footprint. Therefore, research and advances in the function could lead to organizational success in the industry.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Weihang Zhu reports financial support was provided by National Science Foundation. Weihang Zhu reports financial support was provided by National Academies of Sciences Engineering and Medicine. Weihang Zhu reports financial support was provided by US Department of Agriculture.

## Data availability

No data was used for the research described in the article.

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