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ORIGINAL RESEARCH ARTICLE

AI-Driven Process Control for Enhancing Safety and Efficiency in Oil Refining

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ABSTRACT

Artificial Intelligence (AI) is reshaping the oil refining sector by improving process safety, energy efficiency, and product quality. This work evaluates real-time AI applications such as predictive maintenance, anomaly detection, and autonomous process optimization using machine learning, deep learning, reinforcement learning, and natural language processing. A systematic review of recent industrial case studies and simulations shows AI can reduce equipment downtime, emissions, and operational costs while enhancing decision-making and regulatory compliance. Despite these advantages, the adoption of AI in refineries faces challenges such as cybersecurity risks, legacy system integration, and lack of explainable models. Future research should focus on scalable and transparent AI frameworks that align with industry-specific needs.

Keywords: Artificial intelligence; predictive maintenance; process optimization; digital twin; oil refining; anomaly detection

1. Introduction

Oil refining is a high-risk industrial activity involving complex chemical processes conducted under extreme temperature and pressure conditions. Ensuring safe, efficient, and economically viable operation requires advanced monitoring and control systems. In recent years, the emergence of Artificial Intelligence (AI) has opened new possibilities for real-time decision-making, predictive analytics, and autonomous operation in refinery environments. AI is being increasingly recognized as a strategic technology for addressing operational bottlenecks, reducing hazards, and enhancing productivity in the oil and gas sector. Despite the potential of AI to revolutionize refinery operations, several challenges remain. Conventional process control frameworks struggle with the dynamically changing and nonlinear behavior of modern refinery systems. Existing industrial solutions often lack the capacity to analyze large and diverse datasets generated by sensors and instrumentation. This gap highlights the need for AI-based frameworks capable of enabling predictive, adaptive, and data-driven control in real time. The objective of this study is to systematically examine the applications of AI in oil refining, focusing on areas such as predictive maintenance, anomaly detection, process optimization, energy management, and safety enhancement. The review identifies the current limitations of AI adoption in refineries and proposes future research directions for developing scalable and interpretable AI systems tailored to refinery operations.

The disruptive power of AI is transforming industries, impacting the way we address problem solving and decision making [1]. Conventional engineering designs are censored by dynamically complex nature in oil and gas operations, where productivity and safety are still the key factors [1]. AI provides useful instruments to tackle these problems, such as: a) optimization of the production; b) reduction in downtime; c) improved safety; d) support to the exploration and the drilling [2]. The penetration of AI adoption in the oil and gas sector is becoming dynamic, and has passed through various steps like smart drilling, development, refining and pipelines [3]. This paper investigates the versatile use of AI in oil refinery with the perspective of how it can enable processes to be more efficient, safer and sustainable. Oil and gas companies are under growing pressure to consider sustainable practices and embark on a low carbon emission and enhance business operations efficiency [4]. AI-based solutions are proving to be critical to satisfying these end goals, by providing insights and capabilities that were not previously possible without AI. Recently, initiatives have been taken to apply AI-based instruments in predictive maintenance of equipment and early prediction of failure risks in artificial lifting systems [5]. **Figure 1** illustrates the core applications of AI in oil refining, including production optimization, reduced downtime, enhanced safety, and support for exploration. These capabilities contribute to safer, more efficient, and sustainable refinery operations.

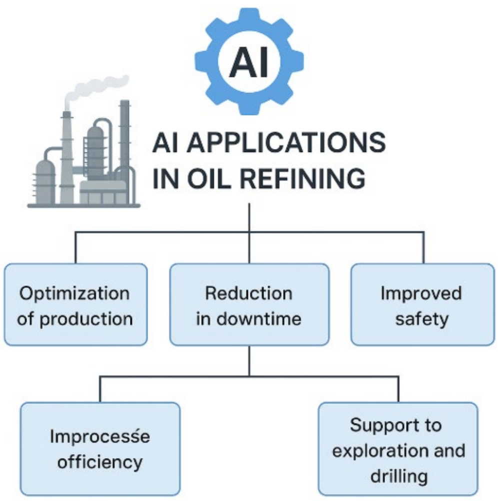

Figure 1. Overview of key AI applications in refining, highlighting their roles in reducing downtime, improving energy efficiency, and enhancing operational safety

Applications of AI in oil and gas industry AI applications in oil and gas seek to increase efficiency and minimize the risk within the set up [6, 7]. The application of machine learning algorithms enables to gain insight into complex processes allowing finer tuning and proactive actions. The digitization of the hydrocarbons industry under Oil and Gas 4.0 provides a platform for innovation and greater public involvement [8]. **Table 1** indicates the summary of AI Applications in Oil Refining.

Table 1. AI Applications in Oil Refining: Summary Table

S.No.	Focus Area	Description	AI Contribution
1	Nature of Oil Refining	Complex, high-risk processes involving high temperatures and pressures.	Enables real-time monitoring and control for safety and compliance.
2	Challenges in Conventional Design	Engineering designs struggle with dynamic complexities in oil & gas operations.	AI offers optimization, safety enhancement, and productivity solutions.
3	Key Applications of AI	Areas such as smart drilling, exploration, refining, pipelines, and lifting systems.	Predictive maintenance, failure risk prediction, and autonomous operations.
4	Business and Sustainability Goals	Growing demand for sustainable, low-emission, and efficient business practices.	AI supports carbon reduction and performance optimization.
5	AI Technologies and Industry 4.0	Integration of machine learning, digitization, and Oil & Gas 4.0 strategies.	Provides predictive analytics, digital twins, and real-time data-driven insights.

2. AI technologies in process control

Oil refining operations are increasingly deploying Artificial Intelligence (AI) technologies to assist with process control, operational efficiency, safety and decision making. These smart applications provide data-based insights, real-time adaptability and automation in the sometimes highly complex, dynamic world of the refining industry. Unfortunately we have to swallow the pill that we are not capable to process that much data by hand through day work and that our only way to make sense of gigantic data volumes is to rely on machine learning algorithms to try to brainstorm what is going on. Machine learning-based predictive models are trained for predicting equipment failure, optimizing process parameters, anomaly detection to enhance overall system performance and reliability [9]. **Figure 2** illustrates the core AI technologies enhancing process control in oil refining. It highlights Machine Learning, Deep Learning, Reinforcement Learning, and NLP as key enablers for predictive analytics, fault detection, adaptive control, and text-based insights. The following AI methods have been applied or have potential for optimizing process control in oil refining:

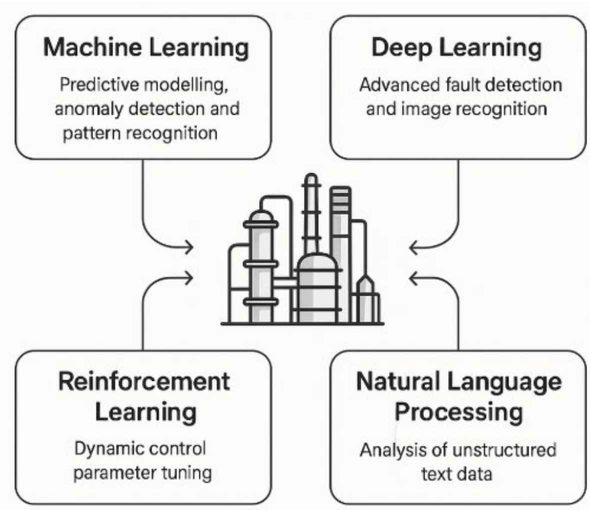

Figure 2. AI Technologies in Process Control for Oil Refining

The application of Artificial Intelligence in refinery process control relies on a diverse set of techniques, each suited to specific operational challenges. Machine Learning provides a foundation for predictive modelling and data-driven optimization, while Deep Learning extends these capabilities to unstructured and high-dimensional datasets such as images and vibration signals. Reinforcement Learning introduces adaptive control mechanisms that learn optimal strategies through interaction with the refinery environment, and Natural Language Processing enables insights from unstructured textual data like maintenance logs and safety reports. Together, these technologies offer complementary strengths in improving system reliability, efficiency, and safety. Their industrial readiness varies based on factors such as data availability, computational requirements, and integration complexity, making it essential to match the right technique to the specific refinery need.

2.1. Machine learning (ML)

Machine learning techniques are increasingly being adapted to process large quantities of historic process data for predictive modelling, anomaly detection and pattern recognition. Temperature, pressure, flow rate, chemical composition etc. These variables can sometimes exhibit some slight trends between each other when they are changing over time and are subject to small correlations that can be caught by the machine learning models in order to predict the behavior of the equipment, optimize the lend on which we operate the equipment and predict failure before the actual occurrence [10]. These instruments ensure that decisions are based on empirical evidence, facilitating both real-time management of operations and long-term planning. Key Performance Index Prediction Several supervised learning methods, e.g., regression and classification, are used to predict multiple KPIs like product yield, energy consumption, and emissions from input variables. During unsupervised learning, for example, clustering and dimension reduction help in recognizing fault states or equipment damages by analyzing deviations in process information without prior knowledge about the system's behavior. Adaptive control strategies learned in the context of the refinery environment using reinforcement learning which learn optimal actions through interaction are employed. These algorithms can be used to optimize control loops by learning to adapt parameters online using data sent back from the system, resulting in improved efficiency and robustness.

2.2. Deep learning

When it comes to processing and interpreting complex data, like sensor signals or images, deep learning (DL), a subtopic of ML, uses multi-layered neural networks. In refinery, deep learning is employed in advanced fault detection using vibration sensors, infrared pictures and others. The systems will be able to detect and alert on indications of equipment failure or a process departure in its early stages, so preventative maintenance can take place and unplanned downtime can be minimized [11]. Deep learning algorithm has also found its application in optimizing control strategy by investigating complicated process variable and control parameters. Such algorithms are also applied for image recognition in refinery monitoring, that can automatically detect safety hazard, equipment breakdown or trespass.

2.3. Reinforcement learning (RL)

RL is an ancient AI paradigm where models learn to make best actions by \trial and error" interactions with a simulated or actual world. In the area of refining, RL is used to tune control parameters such as feed rate, reactor temperature and pressure dynamically to achieve maximum quality of output, energy use, or economic profit [12]. The learning and adaptive features of RL systems are also well suited to complex multivariable operations. This methodology facilitates the application of automatic decision making for refining operations in the context in which an implementation of straightforward control approaches may not work [13].

2.4. Natural language processing (NLP)

NLP allows AI systems to comprehend, interpret, and extract insights from unstructured text data including operator logs, maintenance records, shift reports, and regulatory files. In oil refining, NLP is used to derive value from chemical long narrative, easily pick out issues that reoccur and meet safety and environmental compliance. NLP augments situational awareness inside a refinery by combining human-entered text with sensor data. Using historical maintenance records, NLP is used for detecting commonly occurring failures, not only predicting maintenance requirements but also saving on maintenance cost. [14] NLP has been employed to enforce compliance to industry standards and legal requirements in tasks such as regulatory documents analysis and safety guidelines. **Table 2** indicates AI Technologies in Process Control – Oil Refining.

As a whole, these AI techniques constitute a toolkit that can be employed as to enhance process control in the oil refining industry. They enable the shift from rule based automation towards intelligent, adaptable and self-optimizing systems that can prevent faults and save resources.

Table 2. AI Technologies in Process Control – Oil Refining

S.No.	AI Technology	Purpose/Function	Applications in Refining
1	Machine Learning (ML)	Predictive modelling, anomaly detection and optimization using historical data.	KPI prediction (yield, energy use, emissions), real-time fault detection, and process optimization using regression, classification, and clustering.
2	Deep Learning (DL)	Interpretation of complex sensor signals and visual data using multi-layered neural networks.	Fault detection via vibration/IR sensors, image-based safety monitoring, and optimization of process parameters.
3	Reinforcement Learning (RL)	Learning optimal control strategies via interaction with environment.	Dynamic tuning of reactor parameters, energy optimization, adaptive decision-making in complex scenarios.
4	Natural Language Processing (NLP)	Extraction of insights from unstructured text like logs and reports.	Failure detection from maintenance logs, safety and compliance auditing, issue pattern recognition.
5	AI Toolkit Integration	Combining ML, DL, RL, and NLP for holistic system control.	Self-optimizing systems, proactive maintenance, and intelligent automation beyond traditional control logic.

3. Key applications of AI in oil refining

Artificial intelligence (AI) is changing the face of the oil and gas refining industry by providing smarter, faster and more efficient methods for day-to-day operations. From advanced data analytics to machine learning models to real-time decision-making, AI is used in a broad range of critical areas within the refinery. **Figure 3** illustrates the primary applications of AI in oil refining, highlighting areas such as maintenance, optimization, and quality control. These AI-driven solutions enhance operational efficiency, reduce downtime, and support sustainable practices in refinery processes. The following are the main uses cases which demonstrate of AI's role as a game changer:

Figure 3. Key Applications of AI in Oil Refining

3.1. Predictive maintenance

AI-based predictive maintenance systems rely on sensor data – such as vibration, temperature and pressure readings – to predict/anticipate a pending equipment failure before it actually happens. Machine learning engine examines historical and real-time trends of data to find out early warning indicators of wear, breakdown or component fatigue. With the help of predictive maintenance solutions, refineries can predict the potential for breakdowns and plan for maintenance accordingly, to prevent unscheduled downtime, minimize the costs associated with downtime and extend the life of equipment. AI algorithms are particularly useful in keeping tabs on important equipment, such as pumps, compressors, heat exchangers and reactors—and failures in those components can cause large operational upsets. In addition to cost reduction, AI-driven predictive maintenance also ensures safety by averting accidents involving machine failure. For instance, AI-based algorithms could be applied to the analysis of vibration data generated by rotating equipment in order to identify anomalies indicative of bearing wear or imbalance. Early detection gives maintenance crews the opportunity to take action before the minor problem becomes a big problem. By processing temperature profiles in heat exchangers, AI may determine fouling or corrosion that can inform cleaning or repairs before it's too late. Furthermore, predicting maintenance has proven to minimize unplanned downtime and extend the life of capital assets [15].

3.2. Anomaly detection

Leveraging unsupervised learning and advanced analytics, AI can identify small variances between normal operating parameters that may be indicative of an underlying issue, including leaks, corrosion, fouling, or overheating. Such systems process the multivariable data on an ongoing basis to identify exceptions without relying upon predetermined thresholds or failure modes. Even better, early warning allows for intervention, which will increase safety, decrease risk and prevent downtime. These anomaly detection systems based on AIs act as an early warning system to notify plant operators of potential issues. The technology manages large volumes of data and identifies emergent patterns that could suggest imminent equipment failures [16]. Such timely anomalous detection enables operators to analyze and mitigate issues and prevent their escalation. One of the use cases is anomaly detection, e.g. in heat exchangers performance: unexpected temperature deviations may signal fouled or reduced heat transfer.

3.3. Process optimization

Refining processes Fine tuning the way key operational parameters, like flow rates, reactor temperature and pressure, and the dosages of the various chemicals are used within a wash is just one of the ways in which these technologies can help to address common business challenges found in chemical companies. Additionally, real-time analytics and reinforcement learning allow for constant process refinement, all with the goal of optimizing product yield, increasing throughput, and reducing waste in raw materials. This teachable optimization increases the profitability and guarantees that product specifications are met. Optimizing the process ensures that the operation is efficient and low cost in terms of quality differences. [17] Real-time data analytics and ML algorithms collaborate to optimize process parameters. Such tuning results in increased productivity of desired product and waste and in less energy usage. [18, 19].

3.4. Energy management

Energy AI algorithms help with energy conservation by pinpointing areas in which energy can be saved across gas and heat applications such as distillation columns, fluid catalytic cracking, and hydrocracking. By continuously monitoring and optimizing utility usage (e.g., steam, electricity and fuel) in real time, AI assists in cutting operating costs and minimizing greenhouse gas emissions meeting sustainability goals. AI enables real-time energy optimization throughout the refining process. Artificial intelligence analyses records of patterns in energy usages to determine where energy can be reduced but without affecting production efficiency. Such modifications/maintenance decreases operational costs and minimizes the environmental foot print. AI-optimized energy management in the refinery also has positive impact to the environment outside of the refinery through the reduced carbon emission [20].

3.5. Quality control

Product uniformity is crucial in refining. The AI machines monitor the real-time data of a process and the output characteristic, ensuring automatic adjustment of operating conditions for producing the desired product. By diagnosing quality variation early, AI can help mitigate off-spec production, limit the amount of reprocessing needed and maintain customer satisfaction. Product quality is continually checked by AI-driven systems that give real-time feedback to operators. These systems inherently guarantee species compliance with minimum wastage of off-spec material. This prevents waste, reduces costs, and improves customer satisfaction.

The quality control is improved by the fact that AI is keeping a constant eye on process parameters and product qualities. Moreover, it is not only a process enhancement and less risky for missing products, which amuses the AI [21]. The impact of AI on refining goes far beyond these use cases, into applications such as optimizing the supply chain, cybersecurity and workforce training. This convergence of AI and human intelligence results in refining operations that is more agile and efficient. The implementation of AI into the oil refining industry offers big advantages and plays key role for achieving a better safety, better business efficiency and more profitable [47]. Artificial intelligence: The application of AI for process control is used for the improvement of life cycle operation, energy saving operation [22], and high quality product production [23]. AI techniques are employed to enhance refinery processes [24]. AI enhances safety performance by increasing real-time decision making and decreasing human error. Overall efficiency and profitability is improved by process optimization and waste minimization linked to AI [22]. In addition, AI-based offerings are crucial for addressing the environmental sustainability by minimizing emissions and managing power consumption. Process automation, based on AI, is claimed to improve efficiency and cost-effectiveness in manufacturing environments [25]. **Table 3** indicates the Key Applications of AI in Oil Refining.

Table 3. Summary of major AI applications in oil refining, showing their functions and impact on process reliability, energy use, and sustainability

S.No.	Application Area	Function	Impact in Refining
1	Predictive Maintenance	Uses sensor data (vibration, temperature, pressure) and ML to forecast equipment failures.	Reduces downtime, extends equipment life, increases safety through early detection of faults in pumps, compressors, heat exchangers, etc.
2	Anomaly Detection	Detects subtle deviations in multivariate process data using unsupervised learning.	Provides early warning of leaks, corrosion, fouling or overheating; enables pre-emptive action to prevent escalation.
3	Process Optimization	Applies ML and reinforcement learning for real-time tuning of process parameters.	Improves product yield, reduces raw material waste, and enhances energy efficiency and throughput.
4	Energy Management	Analyses utility consumption patterns to identify energy-saving opportunities.	Optimizes energy use in distillation and cracking, lowers emissions, supports sustainability goals.
5	Quality Control	Monitors real-time process and product data to maintain product uniformity.	Minimizes off-spec output, reduces waste, and improves customer satisfaction and compliance.

Together, these AI applications are transforming the operation of refineries, making them more reliable, efficient, safe, and cost efficient to operate. They represent a major change from reactive to predictive/autonomous operation.

4. Enhancing safety with AI

The role of AI in making oil refineries safer Artificial Intelligence (AI) is being acknowledged as a potent potential catalyst in making oil refining safer. Refineries are high risk, complicated facilities and any failure in them can lead to heavy accidents, environmental problem and loss of production. AI can make travel safer in a more holistic way, by supporting proactive risk management, real-time health monitoring, and predictive intervention. While traditional safety management approaches based on experience and historical data, reactive instead of predictive, AI powered safety is proactive and dynamic. **Figure 4** highlights how AI enhances safety in oil refineries through risk management, predictive maintenance, real-time monitoring, and emergency response.

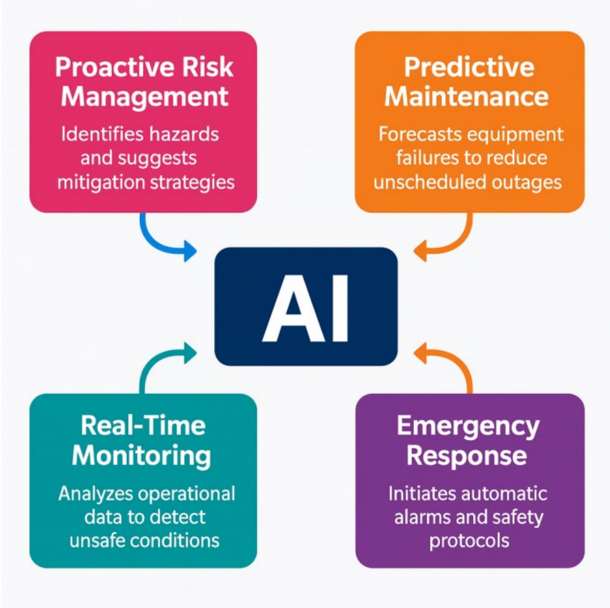

Figure 4. Enhancing Safety with AI in Oil Refineries

AI systems monitor the steady stream of historical and live operational data — temperature, pressure, vibration, and flow rates, for example — searching for patterns or anomalies signaling unsafe conditions that may be emerging. Early indication of challenges such as equipment malfunction, process deviation and system instability allow for corrective action before incidents occur. AI is well equipped to handle large amount of data from different sensors and system and to give an overall presentation of safe allied parameters [26]. These capabilities allow for preventive measures, which is not possible with most conventional monitoring systems [27]. AI empowered predictive maintenance has led to decreases in equipment failures and improvement in safety [6]. AI-based predictive maintains uses machine learning algorithms to predict equipment failure and schedules maintenance. This helps minimize unscheduled outages, lower the likelihood of equipment-related incidents and improve the longevity of asset critical equipment. The AI algorithms analyze the sensor information to identify small changes that might be indicative of an upcoming equipment failure [28, 29]. Moreover, AI-based systems can automatically generate alarm triggers, emergency shutdowns, and best practices in response, minimizing the use of manual decisions in the heat of the moment. These systems contribute to operators' ability to manage the plant in accidents and hence increase general plant safety. Apart from the operational safety itself, AI has an important role in cybersecurity to discover and react to cyber-attacks which can tamper with safety systems or operational control [30]. AI-based algorithms detect potential hazards, evaluate the risk and suggest ways to mitigate it to contribute to a safer work environment [26]. Simulation capabilities, like digital twins, also add to safety planning. A digital twin is a virtual model of a physical system that maintains information about the actual system using real-time data to illustrate a virtual model of the physical object. Refiners can use this to conduct emergency drills and test equipment responses and safety practices virtually without risk. It is great for training, has a role in validating safety measures, and is even used to prepare for unlikely but high-impact episodes. AI-based training simulations can better prepare the workforce to respond to incidents and decrease human error [31]. Systems based on AI give a detailed view of possible risks [26]. On the whole, AI improves the safety of oil refinery operations by not only predicting and preventing accidents, but also by serving as the foundation for smarter, faster, more informed emergency response and decision making in the field. The ability of AI to process huge amounts of data in real-time and provide intelligent decisions is fundamental in the process of transition and effecting change in the maritime transport to achieve efficient, safer and environmental friendly degradation [32]. AI increases safety with proactive risk management, predicting maintenance, real-time monitoring, and better emergency responses. Furthermore, AI is very significant in enhancing protection of cybersecurity [33]. AI can help accurately determine and mitigate possible risks in a timely manner by rapid data analysis [33]. To overcome these difficulties, AI becomes a reinvent force [34]. AI systems are also susceptible to adversarial attacks to deceive or manipulate them, which also pose new cybersecurity challenges [35].

As AI continues to evolve, its role in ensuring safe refinery operations will extend beyond condition monitoring to include autonomous safety logic, cyber-attack prevention, and emergency response training through real-time digital twins. For broader operational advantages such as increased uptime, lower maintenance costs, and improved regulatory compliance, refer to Section 5 on the Benefits of AI-Driven Control.

5. Benefits of AI-Driven control

The use of AI-based control systems in oil refining offers a number of advantages in the operational, economic and safety aspects. The smarter installations take advantage of real-time data analysis, machine learning, and automation to make the whole process more efficient and more responsive. **Figure 5** illustrates the multifaceted benefits of AI-driven control in oil refining, enhancing efficiency, reliability, quality, and sustainability. The key benefits include:

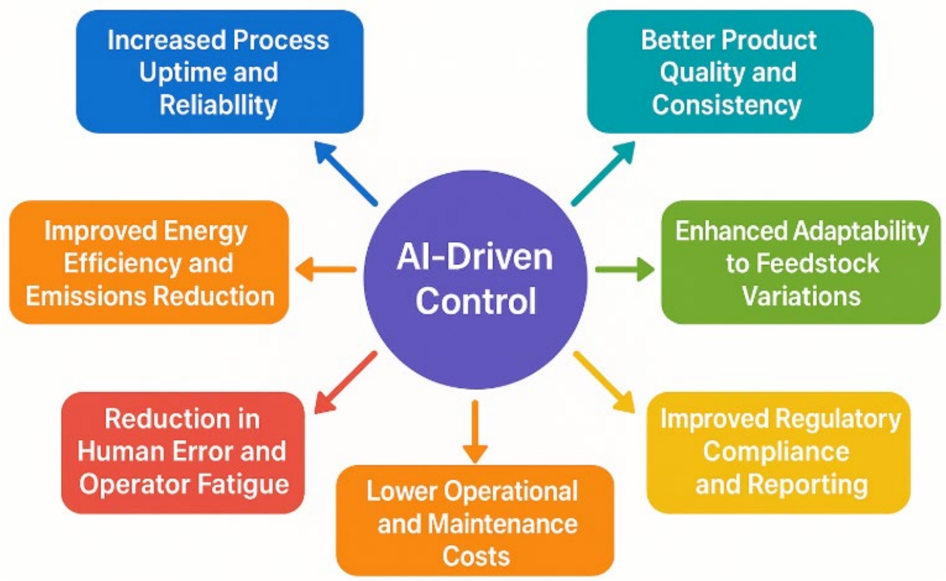

Figure 5. Benefits of AI-Driven Control in Oil Refining

5.1. Increased process uptime and reliability

AI solutions allows for real-time monitoring and predictive diagnostics for early detection of equipment problems and process variation. This proactive strategy means fewer unscheduled outages, less downtime and more reliable and continuous operation of the refining units. AI oversees system health, predicts when maintenance is needed, and adjusts operational settings to maximize uptime and reliability. AI also allows the process parameters to be optimized in real-time depending on the market heat, energy cost and type of product required. These modifications increase a refiner's operational flexibility and raise its profit margin, while allowing a refinery to react rapidly to changing market conditions. AI models can also be trained to find the most energy-efficient operating points, minimize energy consumption and mitigate GHG emissions [36]. Artificial intelligence (AI) continually processes data to uncover energy-saving and emissions-reducing opportunities in a more sustainable refining industry.

Improved Energy Efficiency and Emissions Reduction Artificial Intelligence will optimize the amount of energy being used by detecting and eliminating inefficiencies in the heating, cooling, and separation stages. 2) AI can also contribute to environmental sustainability while reducing energy waste and maximizing resource usage i.e. by reducing energy wastages and through improved resource utilizations AI can decrease operational costs as well as environment supports reducing both emissions and waste generation.

Better product quality and consistency With AI, process variables can be tightly controlled, ultimately contributing to more consistent product quality and specification compliance. Real-time monitoring and automatic setup change to minimize variation, minimize rework needs, and deliver final products that meet tough quality standards, time after time.

5.2. Reduction in human error and operator fatigue

By automating complex decision making and routine monitoring, that AI makes it possible to rely less on human judgement, particularly during long shifts or under conditions of stress. As a result, less oversight, fatigue, and misinterpretation-related errors are generated, process safety and accuracy is increased. AI helps automate decision-making, scheduling and controlling, reducing the pressure on human controllers. The AI-based automation can help in automating the routine tasks and enable the human operators to actively engage in strategic decision making, troubleshooting, and complex problem investigation [37].

5.3. Improved regulatory compliance and reporting

AI makes compliance easier as it provides compliance support apt to make an easier collection, analysis and documentation of data needed in regards to environmental and safety regulations. These reports help satisfy EPA, OSHA, and local environmental agency regulator, audit, and compliance monitoring requirements.

In the context of wastewater treatment plants AI outperforms conventional methods such as simulation, prediction, control, and adaptive technology to fulfil challenging tasks of minimizing energy consumption and emissions and to optimize resource recovery [38]. Artificial intelligence methods are applied for process optimization, water quality enhancement, cost reduction, and energy-saving [39]. AI's capacity of learning from experience permits intelligent agents to interpret their environment and take decisions to be maximally likely to reach the specified meanings aimed [40]. AI can drive scientific discoveries and make accurate predictions at a faster pace [41]. In total, using AI in the oil refining process enables safer, efficient and more sustainable operations.

5.4. Enhanced adaptability to feedstock variations

Crude oil is frequently difficult to refine as it has varying chemical structures. Feedstock properties can be analyzed by AI models much more quickly and new processing conditions can be applied real-time, thus ensuring steady-state optimal performance. This flexibility provides an even quality of the product, and it provides the highest possible production even if the characteristics of the raw material vary. Using advanced algorithm and big data analysis, AI maximizes operating parameters, improves energy efficiency, and minimizes risk of asset failures. This integration will result in increased safety, environmental performance, and profitability in the refining sector [42]. AI-based data pipelines, real time monitoring, and adaptive reporting can be readily accommodated in evolving regulations [43]. AI methods have also been used in the search for new electro catalysts for renewable energy storage and utilization [45].

5.5. Lower operational and maintenance costs

Using predictive maintenance, improved equipment performance, and advanced energy monitoring, AI helps decrease the amount of reactive maintenance that needs to be done, which is more expensive than preventative maintenance. This not only has positive effects on maintenance-related expenses, but it also contributes to higher asset utilization, longer equipment life, and improved general operability and cost efficiency. AI is re-engineering virtually every part of business, and there can be little doubt that companies investing in AI have generated a significant competitive edge by way of cost savings, revenue, and asset utilization [45]. AI use cases can include new opportunities to improve energy efficiency and combustion; predictive maintenance; and decision-making, which combined can help refineries save costs and improve profitability. By detecting faults and failures rapidly and in real time, AI substantially decreases downtime and keeps production disturbances to a minimum, which translates into higher efficiency and cost cutting [46]. **Table 4** shows the Benefits of AI-Driven Control in Oil Refining.

Table 4. Benefits of AI-Driven Control in Oil Refining

S.No.	Benefit Area	Function	Impact in Refining
1	Increased Uptime & Reliability	Real-time monitoring, predictive diagnostics, and dynamic parameter adjustments.	Minimizes downtime, enhances energy efficiency, and ensures process continuity and adaptability to market needs.
2	Reduction in Human Error	Automation of routine decisions and monitoring; support to operators.	Reduces operator fatigue, prevents oversight-related errors, and improves safety and focus on strategic tasks.
3	Regulatory Compliance	Automated data collection, documentation, and intelligent reporting.	Eases audit processes, improves safety/environmental compliance, and supports smart wastewater treatment.
4	Adaptability to Feedstock Variations	AI analysis of crude properties and adaptive control settings.	Maintains optimal performance and product quality despite variable feedstock; ensures profitability and safety.
5	Lower O&M Costs	Predictive maintenance, real-time fault detection, and performance optimization.	Extends equipment life, minimizes downtime, reduces costs, and boosts asset utilization and competitiveness.

AI improves safety through equipment monitoring, predicting potential failures with corresponding g process optimization helping to minimize risk [47]. AI improves process safety by monitoring sensors and devices real-time. These advantages combine into AI-based controlling systems, a key tool in modern, competitive and sustainable oil refining plants.

6. Challenges and limitations

AI adoption in oil refining brings significant benefits but also faces several interrelated barriers. These challenges stem from technical, organizational, and regulatory issues that can impact implementation and long-term sustainability.

6.1. Data and infrastructure constraints

Many refineries rely on legacy equipment that lacks modern sensing and data acquisition capabilities. Integrating these systems with AI requires substantial investment in digital infrastructure and real-time data pipelines. Inadequate data quality and incompatibility between systems make it difficult for AI models to learn, adapt, and perform reliably.

6.2. Cybersecurity and system vulnerability

AI integration increases system connectivity, which expands the attack surface for cyber threats. Without strong cybersecurity measures such as network segmentation, encryption, and intrusion monitoring, AI-enabled systems may be exposed to unauthorized access, data breaches, or operational manipulation.

6.3. Workforce and explainability gaps

AI-driven control systems require expertise in data science, machine learning, and process engineering. Many refineries face a lack of skilled personnel to manage and maintain these systems. In addition, complex AI models—especially deep learning-based systems—often function as "black boxes," making it difficult for operators to understand decision-making processes and trust automated recommendations.

6.4. Regulatory and compliance uncertainty

There is still no standardized framework governing the deployment of AI in safety-critical sectors like oil refining. Ambiguity in certification, accountability, and liability discourages widespread adoption of AI tools, especially when they are used in core process control, safety, and environmental compliance applications.

The swift advancement of AI-integrated technologies is significantly promoting the use of innovative cooling strategies in engines to improve thermal efficiency and minimize emissions from combustion. Among these strategies, thermal management using phase change materials (PCMs) has gained prominence for its superior performance over traditional techniques like forced convection and heat pipes, especially during high-power applications [59]. In one study, nine thermal configurations were tested using controlled flow simulations on silicon/copper-based printed circuit boards. The inclusion of copper in the substrate led to notable reductions in chip temperature. Even at airflow velocities ranging from 3 m/s to 5 m/s and under ambient temperatures between 30 °C and 47 °C, integrated circuit cooling improved significantly, with temperature decreases ranging from 1.50 °C to 11.12 °C [60].

Among the materials evaluated, n-Eicosane proved to be the most effective PCM, showing exceptional heat absorption and enthalpy characteristics by lowering the lowest boiling point from 53.234 °C to 51.520 °C. This surpassed the performance of paraffin wax and ATP 78, which achieved only 0.5 °C and 1.35 °C temperature reductions, respectively, when employed in minichannel heat sink configurations [61]. Current trends in thermal management research are exploring advanced approaches such as minijet impingement cooling [62], the use of nanofluids to enhance thermal conductivity [63], water-based cooling systems [64], and twisted tape inserts to intensify heat transfer [65–67]. These solutions are increasingly being combined with AI-based control frameworks to enable real-time thermal regulation in domains such as electronic device cooling, biodiesel combustion systems, solar thermal systems, substrate cooling, vehicle aerodynamics, and smart control algorithms like fuzzy logic systems [68–77].Moreover, continued technological development is addressing the optimization of thermal management in wind turbines, improved HVACR component arrangement, adsorption-based cooling systems, thermal safety in transportation, and surface treatment techniques to maximize heat dissipation [78–92]. Such studies not only reinforce the practical application of PCM-based cooling for integrated circuits but also aid in improving fuel additives and thermal handling in structural systems including steel plates, welds, and complex curved surfaces [93–101].

In internal combustion engines, a promising approach involves using Multi-Type Phase Change (MTPC) materials, which provide robust cooling under variable temperature loads. Deep learning models are also being utilized to identify surface defects in geological materials, while the design of microchannel heat sinks continues to evolve to boost transient heat transfer efficiency. In parallel, emission reduction strategies such as biodiesel blending, catalytic after-treatment, and the application of solar collectors fitted with trapezoidal ducts and delta-wing vortex generators have demonstrated superior thermal performance compared to conventional rectangular ducts [102–108].Other significant developments include AI-based predictive maintenance for industrial mixer shafts, PCM-enabled thermal management for portable devices, and finite element analysis (FEA) techniques for optimizing mixer shaft structures [109–110]. Additionally, the use of perforated twisted tapes has led to improvements in engine thermal performance [111]. Overall, artificial intelligence is emerging as a key enabler in minimizing the environmental footprint of mining operations, enhancing system modelling (e.g., in vibratory bowl feeders with paddle shafts), and pushing forward the development of intelligent, eco-efficient engine cooling and design solutions [112–118].

Overcoming these hurdles is essential to realize AI's potential in oil refining. Breaking down the technical or organizational roadblocks and enabling a favorable regulatory and cybersecurity landscape allows the industry to step into a more intelligent and sustainable operation mode with assurance. **Table 5** explains challenges and limitations of AI in Oil Refining.

Table 5. Challenges and Limitations of AI in Oil Refining

S.No.	Challenge Area	Description	Impact on Refining Operations
1	Data Availability and Integration	Legacy systems lack sensor coverage, unified structures, and real-time data quality.	Hinders training of AI models and delays implementation of intelligent systems.
2	Cybersecurity Risks	AI increases connectivity, exposing systems to breaches, unauthorized access, and control failures.	Compromises safety and reliability; necessitates advanced threat mitigation protocols.
3	Lack of Transparency (Black-Box Models)	AI decisions are hard to interpret, limiting operator trust and acceptance.	Reduces confidence in AI use, especially in safety-critical operations; calls for explainable AI.
4	Skilled Workforce Shortage	AI integration requires expertise in ML, process engineering, and cybersecurity.	Slows AI deployment, impacts performance and long-term sustainability of AI systems.
5	Data Accuracy and Integrity	Outdated or inaccurate data leads to poor AI performance and unreliable decisions.	Requires constant monitoring, updating, and validation of data sources for accurate outcomes.
6	Regulatory Uncertainty	Lack of clear legal and safety standards for AI in oil refining.	Discourages investment and adoption for critical control systems; requires industry-government frameworks.

7. Future outlook

The dawn of AI in oil refining is set to transform the industry with increased digitalization, transparency and collaboration between sites and systems. In the near future, a dozen new technologies and research approaches will be key to unlocking the true power of AI in extraction.

7.1. Digital twins with real-time optimization and safety simulation

Digital twins — computerized replicas of physical objects and processes — are set to be a centerpiece of AI incorporation in refineries. Through the combination of real-time sensor data and simulation models, digital twins for refineries allow for predictive control, fault simulation and dynamic optimization of refining units. They provide a low-risk and low-cost environment for testing new control strategies, predicting

7.2. Federated learning for secure and collaborative model training

Federated learning enables AI models to be developed at a number of different refineries or within various departments without the need to send sensitive operating data to a centralized server. This phone-based approach enhances data privacy, respects intellectual property (IP) boundaries and allows cross-site collaboration. Through the combination of information across datasets and keeping data confidential, federated learning contributes to the development of robust and generalized AI models for various plant conditions.

7.3. Explainable AI (XAI) for trustworthy and transparent decision-making

Explainable AI systems will be increasingly necessary as AI is more and more vital to operations. Such models will be interpretable, i.e. not only predict well but also explain in human-understandable terms what their outputs are based on. For oil refineries, it is important to satisfy regulators, for operators to rely on, and for the assessment of risk. Studies should focus on the development of interpretable models that integrate data-mining-driven and domain-driven findings.

7.4. Focus on refining-specific ai solutions and real-time interfaces

Next-generation AI research must tackle the unique challenges of oil refining—multi-phase flow, high temperature, and product quality variation—to make sure AI can be done in a useful and relevant way. Real-time control interfaces and domain-specific algorithms integrated into AI systems promote faster decision-making, better integration with existing infrastructure, and more accurate process tuning. Ultimately, AI's future in oil refining will be forged by intelligent, collaborative and transparent systems. Pushing the capabilities of digital twins, federated learning and explainable AI, and targeting real-time, process-specific applications, the industry can increasingly drive towards a safer, smarter and more sustainable operation. Interdisciplinary collaboration between data scientists, engineers and the policy making body will be critical to pushing the frontier and deploying AI responsibly at scale.

8. Conclusion

Artificial Intelligence is reshaping oil refining through intelligent process control, real-time monitoring, and predictive analytics. The evidence reviewed demonstrates measurable benefits such as reduced equipment failures, improved energy efficiency, and enhanced operational safety. AI-based predictive maintenance has enabled early fault detection in critical assets, translating into lower downtime and extended equipment life. Similarly, reinforcement learning and digital twin technologies have optimized multi-variable operational parameters, supporting higher product yield and consistency while minimizing waste and emissions.

Despite these advantages, challenges such as system interoperability, cybersecurity vulnerabilities, data sparsity, and limited domain-specific expertise hinder full-scale implementation. To address these gaps, refineries should prioritize the integration of scalable sensor networks, cybersecurity frameworks, and workforce upskilling in AI and data-driven decision making. Adoption of explainable AI models can further reinforce operator trust and regulatory acceptance.

Future research should focus on multi-physics hybrid digital twins that combine AI-based predictions with physical models for refinery-wide optimization. Another promising direction is AI-driven refinery simulations that evaluate energy use under dynamic feedstock conditions, integrating sustainability metrics for low-carbon operations. Collaborative platforms using federated learning can enable secure cross-site model training, advancing predictive maintenance and decision support without compromising proprietary data.

As the sector moves toward autonomous and distributed control architectures, the convergence of AI, process engineering, and industrial cybersecurity will define the next phase of refinery modernization. Continued interdisciplinary research and deployment will be critical to achieving safer, smarter, and more environmentally conscious refining systems.

Author Contributions

The authors contributed to this work as follows: **Manjusha Tatiya** led the conceptualization, methodology, data curation, and preparation of the original draft. **Babaso A. Shinde** was responsible for software implementation, validation, visualization, and formal analysis. **Navnath B. Pokale** contributed to

the investigation, supervision of AI and data integration aspects, and manuscript review. **Mahesh Sarada** managed resources, data collection, and project administration. **Mahesh M. Bulhe** provided funding support, assisted with infrastructure, and reviewed the technical sections. **Govindrajan Murali** supervised the process engineering components, critically reviewed the manuscript, and contributed essential resources. **Vidhi Rajendra Kadam** assisted in the preparation of tables and figures, carried out an extensive literature review, and edited technical segments. **Anant Sidhappa Kurhade and Shital Yashwant Waware** offered overall supervision and conceptual guidance, reviewed and edited the manuscript, served as the corresponding author, and approved the final version for publication.

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Conflict of interest

The authors declare no conflict of interest

References

1. Arinze CA, Izionworu VO, Isong DE, Daudu CD, Adefemi A. Integrating artificial intelligence into engineering processes for improved efficiency and safety in oil and gas operations. Open Access Research Journal of Engineering and Technology [Internet]. 2024 Mar 19 [cited 2025 Feb];6(1):39. Available from: https://doi.org/10.53022/oarjet.2024.6.1.0012
2. 2. Li JX, Zhang T, Zhu Y, Chen Z. Artificial General Intelligence (AGI) for the oil and gas industry: a review. arXiv (Cornell University) [Internet]. Cornell University; 2024 Jun 1 [cited 2025 Feb]; Available from: https://arxiv.org/abs/2406.00594
3. Deif AM, Vivek T. Understanding AI Application Dynamics in Oil and Gas Supply Chain Management and Development: A Location Perspective. HighTech and Innovation Journal [Internet]. 2022 Mar 15 [cited 2025 Feb];3:1. Available from: https://doi.org/10.28991/hij-sp2022-03-01
4. Waqar A, Othman I, Shafiq N, Mansoor MS. Applications of AI in oil and gas projects towards sustainable development: a systematic literature review. Artificial Intelligence Review [Internet]. 2023 Mar 23 [cited 2025 Feb];56(11):12771. Available from: https://doi.org/10.1007/s10462-023-10467-7
5. D'Almeida AL, Bergiante NCR, Ferreira G de S, Leta FR, Lima CB de C, Lima GBA. Digital transformation: a review on artificial intelligence techniques in drilling and production applications. The International Journal of Advanced Manufacturing Technology [Internet]. Springer Science+Business Media; 2022 Jan 22 [cited 2025 Feb];119:5553. Available from: https://doi.org/10.1007/s00170-021-08631-w
6. Hong L, Yu H, Cao N, Tian H, Cheng S. Applications of Artificial Intelligence in Oil and Gas Development. Archives of Computational Methods in Engineering [Internet]. 2020 Jan 16 [cited 2025 Feb];28(3):937. Available from: https://doi.org/10.1007/s11831-020-09402-8
7. Chernikov AD, Eremin NA, Stolyarov VE, Sboev A, Semenova-Chashchina OK, Fitsner LK. Application of artificial intelligence methods for identifying and predicting complications in the construction of oil and gas wells: problems and solutions. Georesursy [Internet]. 2020 Sep 30 [cited 2025 Feb];22(3):87. Available from: https://doi.org/10.18599/grs.2020.3.87-96
8. Pandey YN, Rastogi A, Kainkaryam S, Bhattacharya S, Saputelli L. Opportunities, Challenges, and Future Trends. In: Apress eBooks [Internet]. 2020 [cited 2025 Feb]. p. 259. Available from: https://doi.org/10.1007/978-1-4842-6094-4_8
9. Wu D, Jennings C, Terpenny J, Gao RX, Kumara S. A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests. Journal of Manufacturing Science and Engineering [Internet]. 2017 Mar 28 [cited 2025 Feb];139(7). Available from: https://doi.org/10.1115/1.4036350
10. Pereira PC. Hidden Value in Maintenance System Data: Using Machine Learning to Correlate and Predict the Risk of Asset Failures. In: Offshore Technology Conference [Internet]. 2020 [cited 2025 Jun]. Available from: https://doi.org/10.4043/30730-ms
11. Hoffmann M, Wildermuth S, Gitzel R, Boyaci A, Gebhardt J, Kaul H, Amihai I, Forg B, Suriyah M, Leibfried T, Stich V, Hicking J, Bremer M, Kaminski L, Beverungen D, Heiden P zur, Tornede T. Integration of Novel Sensors and Machine Learning for Predictive Maintenance in Medium Voltage Switchgear to Enable the Energy and Mobility Revolutions. Sensors [Internet]. Multidisciplinary Digital Publishing Institute; 2020 Apr 8 [cited 2025 Jun];20(7):2099. Available from: https://doi.org/10.3390/s20072099

12. Shipman WJ. Learning to Tune a Class of Controllers with Deep Reinforcement Learning. Minerals [Internet]. 2021 Sep 9 [cited 2025 May];11(9):989. Available from: https://doi.org/10.3390/min11090989
13. Schulze K. Adaptive Multivariable Control -An Integrated Concept-. IFAC Proceedings Volumes [Internet]. 1997 May 1 [cited 2025 Jan];30(6):1191. Available from: https://doi.org/10.1016/s1474-6670(17)43523-3
14. Bachate R, Sharma A. Acquaintance with Natural Language Processing for Building Smart Society. E3S Web of Conferences [Internet]. 2020 Jan 1 [cited 2025 Feb];170:2006. Available from: https://doi.org/10.1051/e3sconf/202017002006
15. Gowekar GS. Artificial intelligence for predictive maintenance in oil and gas operations. World Journal of Advanced Research and Reviews [Internet]. 2024 Sep 14 [cited 2025 Feb];23(3):1228. Available from: https://doi.org/10.30574/wjarr.2024.23.3.2721
16. Rojas L, Peña Á, García J. AI-Driven Predictive Maintenance in Mining: A Systematic Literature Review on Fault Detection, Digital Twins, and Intelligent Asset Management. Applied Sciences [Internet]. 2025 Mar 19 [cited 2025 Jun];15(6):3337. Available from: https://doi.org/10.3390/app15063337
17. Anozie UC, Pieterson K, Onyenahazi OB, Chukwuebuka UO, Ekeocha PC. Integration of IoT technology in lean manufacturing for real-time supply chain optimization. International Journal of Science and Research Archive [Internet]. 2024 Aug 17 [cited 2025 Feb];12(2):1948. Available from: https://doi.org/10.30574/ijsra.2024.12.2.1498
18. Shukla BK, Maurya N, Sharma M. Advancements in Sensor-Based Technologies for Precision Agriculture: An Exploration of Interoperability, Analytics and Deployment Strategies. 2023 Nov 15 [cited 2025 Jun];22. Available from: https://doi.org/10.3390/ecsa-10-16051
19. Kumar S, Gopi T, Harikeerthana N, Gupta MK, Gaur V, Królczyk G, Wu C. Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control. Journal of Intelligent Manufacturing [Internet]. 2022 Oct 10 [cited 2025 Feb];34(1):21. Available from: https://doi.org/10.1007/s10845-022-02029-5
20. Olawade DB, Wada OZ, David-Olawade AC, Fapohunda O, Ige AO, Ling J. Artificial intelligence potential for net zero sustainability: Current evidence and prospects. Next Sustainability [Internet]. 2024 Jan 1 [cited 2025 Feb];4:100041. Available from: https://doi.org/10.1016/j.nxsust.2024.100041
21. Malik S, Muhammad K, Waheed Y. Artificial intelligence and industrial applications-A revolution in modern industries. Ain Shams Engineering Journal [Internet]. 2024 Jun 5 [cited 2025 Feb];15(9):102886. Available from: https://doi.org/10.1016/j.asej.2024.102886
22. Jin D, Ocone R, Jiao K, Xuan J. Energy and AI. Energy and AI [Internet]. 2020 Apr 20 [cited 2025 Feb];1:100002. Available from: https://doi.org/10.1016/j.egyai.2020.100002
23. Sundaram S, Zeid A. Artificial Intelligence-Based Smart Quality Inspection for Manufacturing. Micromachines [Internet]. 2023 Feb 27 [cited 2025 Feb];14(3):570. Available from: https://doi.org/10.3390/mi14030570
24. Chen J. A System of Multistep Self-Learning Forecast and its Application on Oil Refining Industry. Advanced materials research [Internet]. 2012 Dec 1 [cited 2025 Feb];1675. Available from: https://doi.org/10.4028/www.scientific.net/amr.605-607.1675
25. Gavade D. AI-driven process automation in manufacturing business administration: efficiency and cost-efficiency analysis. IET conference proceedings [Internet]. 2024 Feb 27 [cited 2025 Jun];2023(44):677. Available from: https://doi.org/10.1049/icp.2024.1038
26. Bajwa A. AI-based Emergency Response Systems: A Systematic Literature Review on Smart Infrastructure Safety. SSRN Electronic Journal [Internet]. 2025 Jan 1 [cited 2025 May]; Available from: https://doi.org/10.2139/ssrn.5171521
27. Akhtar ZB. Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. Metaverse [Internet]. 2024 Jul 4 [cited 2025 May];5(2):2731. Available from: https://doi.org/10.54517/m.v5i2.2731
28. abbas asad. AI for Predictive Maintenance in Industrial Systems. 2024 Jan 28 [cited 2025 Feb]; Available from: https://doi.org/10.31219/osf.io/vq8zg
29. Shiboldenkov VA, Nesterova K. The smart technologies application for the product life-cycle management in modern manufacturing systems. MATEC Web of Conferences [Internet]. 2020 Jan 1 [cited 2025 Feb];311:2020. Available from: https://doi.org/10.1051/matecconf/202031102020
30. Park J, Kang D. Artificial Intelligence and Smart Technologies in Safety Management: A Comprehensive Analysis Across Multiple Industries. Applied Sciences [Internet]. 2024 Dec 20 [cited 2025 Jun];14(24):11934. Available from: https://doi.org/10.3390/app142411934
31. Bates DW, Levine DM, Syrowatka A, Kuznetsova M, Craig KJT, Rui A, Jackson GP, Rhee K. The potential of artificial intelligence to improve patient safety: a scoping review. npj Digital Medicine [Internet]. Nature Portfolio; 2021 Mar 19 [cited 2025 Feb];4(1). Available from: https://doi.org/10.1038/s41746-021-00423-6
32. Durlik I, Miller T, Kostecka E, Kozlovska P, Ślączka W. Enhancing Safety in Autonomous Maritime Transportation Systems with Real-Time AI Agents. Applied Sciences [Internet]. 2025 Apr 30 [cited 2025 May];15(9):4986. Available from: https://doi.org/10.3390/app15094986

33. Binhammad MHY, Alqaydi S, Othman A, Abuljadayel LH. The Role of AI in Cyber Security: Safeguarding Digital Identity. Journal of Information Security [Internet]. 2024 Jan 1 [cited 2025 May];15(2):245. Available from: https://doi.org/10.4236/jis.2024.152015
34. Kalogiannidis S, Kalfas D, Papaevangelou O, Giannarakis G, Chatzitheodoridis F. The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece. Risks [Internet]. 2024 Jan 23 [cited 2025 Jun];12(2):19. Available from: https://doi.org/10.3390/risks12020019
35. Roshanaei M, Khan MR, Sylvester NN. Navigating AI Cybersecurity: Evolving Landscape and Challenges. Journal of Intelligent Learning Systems and Applications [Internet]. 2024 Jan 1 [cited 2025 Jun];16(3):155. Available from: https://doi.org/10.4236/jilsa.2024.163010
36. Yazdi M, Zarei E, Adumene S, Beheshti A. Navigating the Power of Artificial Intelligence in Risk Management: A Comparative Analysis. Safety [Internet]. 2024 Apr 26 [cited 2025 Jun];10(2):42. Available from: https://doi.org/10.3390/safety10020042
37. Akinrinmade AO, Adebile TM, Ezuma-Ebong C, Bolaji K, Ajufo A, Adigun AO, Mohammad M, Dike JC, Okobi OE. Artificial Intelligence in Healthcare: Perception and Reality. Cureus [Internet]. Cureus, Inc.; 2023 Sep 20 [cited 2025 Feb]; Available from: https://doi.org/10.7759/cureus.45594
38. Capodaglio AG, Callegari A. Use, Potential, Needs, and Limits of AI in Wastewater Treatment Applications. Water [Internet]. 2025 Jan 10 [cited 2025 Jun];17(2):170. Available from: https://doi.org/10.3390/w17020170
39. Alenezi A, Alabaiadly Y. Artificial Intelligence Applications in Water Treatment and Desalination: A Comprehensive Review. Water [Internet]. Multidisciplinary Digital Publishing Institute; 2025 Apr 14 [cited 2025 Jun];17(8):1169. Available from: https://doi.org/10.3390/w17081169
40. Kamali M, Appels L, Yu X, Aminabhavi TM, Dewil R. Artificial intelligence as a sustainable tool in wastewater treatment using membrane bioreactors. Chemical Engineering Journal [Internet]. 2020 Dec 10 [cited 2025 Feb];417:128070. Available from: https://doi.org/10.1016/j.cej.2020.128070
41. Kulikova EYu, Sulimin V, Shvedov V. Artificial intelligence for ambient air quality control. E3S Web of Conferences [Internet]. 2023 Jan 1 [cited 2025 Apr];419:3011. Available from: https://doi.org/10.1051/e3sconf/202341903011
42. Bartram SM, Branke J, Motahari M. Artificial Intelligence in Asset Management. SSRN Electronic Journal [Internet]. 2020 Jan 1 [cited 2025 Jun]; Available from: https://doi.org/10.2139/ssrn.3692805
43. Vangala BL. AI-Enabled Data Engineering Solutions for Regulatory Compliance in Automotive Industry: Simplifying the Regulatory Landscapes. International Journal of Innovative Research in Science Engineering and Technology [Internet]. 2025 May 3 [cited 2025 Jun];14(5). Available from: https://doi.org/10.15680/ijirset.2025.1405003
44. Wu CJ, Raghavendra R, Gupta U, Acun B, Ardalani N, Maeng K, Chang G, Behram FA, Huang J, Bai C, Gschwind M, Gupta A, Ott M, Мельников AC, Candido S, Brooks DJ, Chauhan G, Lee B, Lee HHS, Akyildiz B, Balandat M, Spisak J, Jain R, Rabbat M, Hazelwood K. Sustainable AI: Environmental Implications, Challenges and Opportunities. arXiv (Cornell University) [Internet]. 2021 Jan 1 [cited 2025 Feb]; Available from: https://arxiv.org/abs/2111.00364
45. Dash R, McMurtrey ME, Rebman C, Kar UK. Application of Artificial Intelligence in Automation of Supply Chain Management. Journal of Strategic Innovation and Sustainability [Internet]. 2019 Jul 18 [cited 2025 Feb];14(3). Available from: https://doi.org/10.33423/jsis.v14i3.2105
46. Nahar S. Modeling the effects of artificial intelligence (AI)-based innovation on sustainable development goals (SDGs): Applying a system dynamics perspective in a cross-country setting. Technological Forecasting and Social Change [Internet]. 2024 Jan 20 [cited 2025 Jun];201:123203. Available from: https://doi.org/10.1016/j.techfore.2023.123203
47. Bello O, Teodoriu C, Yaqoob T, Oppelt J, Holzmann J, Obiwanne A. Application of Artificial Intelligence Techniques in Drilling System Design and Operations: A State of the Art Review and Future Research Pathways. SPE Nigeria Annual International Conference and Exhibition [Internet]. 2016 Jul 6 [cited 2025 Feb]; Available from: https://doi.org/10.2118/184320-ms
48. Tariq Z, Aljawad MS, Hasan A, Murtaza M, Mohammed EA, El-Husseiny A, Alarifi SA, Mahmoud M, Abdulraheem A. A systematic review of data science and machine learning applications to the oil and gas industry. Journal of Petroleum Exploration and Production Technology [Internet]. Springer Nature; 2021 Sep 24 [cited 2025 Feb];11(12):4339. Available from: https://doi.org/10.1007/s13202-021-01302-2
49. Koroteev D, Tekić Ž. Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future. Energy and AI [Internet]. 2020 Dec 23 [cited 2025 Feb];3:100041. Available from: https://doi.org/10.1016/j.egyai.2020.100041
50. Pawar S, Dhumal V. The role of technology in transforming leadership management practices. Multidisciplinary Reviews [Internet]. 2024 Jan 18 [cited 2025 Jun];7(4):2024066. Available from: https://doi.org/10.31893/multirev.2024066
51. Emaminejad N, North AM, Akhavian R. Trust in AI and Implications for the AEC Research: A Literature Analysis. arXiv (Cornell University) [Internet]. 2022 Jan 1 [cited 2025 Jan]; Available from: https://arxiv.org/abs/2203.03847

52. Sinha S, Lee YM. Challenges with developing and deploying AI models and applications in industrial systems. Discover Artificial Intelligence [Internet]. 2024 Aug 16 [cited 2025 Jun];4(1). Available from: https://doi.org/10.1007/s44163-024-00151-2
53. Polemi N, Praça I, Kioskli K, Bécue A. Challenges and efforts in managing AI trustworthiness risks: a state of knowledge. Frontiers in Big Data [Internet]. 2024 May 9 [cited 2025 Jun];7. Available from: https://doi.org/10.3389/fdata.2024.1381163
54. Pery A, Rafiei M, Simon M, Aalst WMP van der. Trustworthy Artificial Intelligence and Process Mining: Challenges and Opportunities. arXiv (Cornell University) [Internet]. 2021 Jan 1 [cited 2025 May]; Available from: https://arxiv.org/abs/2110.02707
55. Yu L, Li Y, Fan F. Employees' Appraisals and Trust of Artificial Intelligences' Transparency and Opacity. Behavioral Sciences [Internet]. 2023 Apr 20 [cited 2025 Jun];13(4):344. Available from: https://doi.org/10.3390/bs13040344
56. Choung H, David P, Ross A. Trust in AI and Its Role in the Acceptance of AI Technologies. International Journal of Human-Computer Interaction [Internet]. 2022 Apr 20 [cited 2025 Jun];39(9):1727. Available from: https://doi.org/10.1080/10447318.2022.2050543
57. Petković D. It is Not "Accuracy vs. Explainability"—We Need Both for Trustworthy AI Systems. IEEE Transactions on Technology and Society [Internet]. 2023 Jan 30 [cited 2025 Feb];4(1):46. Available from: https://doi.org/10.1109/tts.2023.3239921
58. Knowles B, Richards JT. The Sanction of Authority: Promoting Public Trust in AI. arXiv (Cornell University) [Internet]. 2021 Jan 1 [cited 2025 Apr]; Available from: https://arxiv.org/abs/2102.04221
59. Kurhade A, Talele V, Rao TV, Chandak A, Mathew VK. Computational study of PCM cooling for electronic circuit of smart-phone. Materials Today: Proceedings. 2021 Jan 1;47:3171-6.
60. Kurhade AS, Amruth E, Joshi PS, Kondhalkar GE, Jadhav PA, Murali G, Mahajan RG, Waware SY. Enhancing Flat-Plate Solar Collector Efficiency: A Numerical Study. jmmf [Internet]. 2025 Apr. 16 [cited 2025 Apr. 28];73(4):1065-76.
61. Kurhade AS, Murali G. Thermal control of IC chips using phase change material: A CFD investigation. International Journal of Modern Physics C. 2022 Dec 28;33(12):2250159.
62. Kurhade AS, Murali G, Rao TV. CFD approach for thermal management to enhance the reliability of IC chips. Int J Eng Trends Technol. 2022;71(3):65-72.
63. Waware SY, Kore SS, Kurhade AS, Prakashrao S. Innovative Heat Transfer Enhancement in Tubular Heat Exchanger: An.
64. Kurhade AS, Biradar R, Yadav RS, Patil P, Kardekar NB, Waware SY, Munde KH, Nimbalkar AG, Murali G. Predictive placement of IC chips using ANN-GA approach for efficient thermal cooling. J Adv Res Fluid Mech Therm Sc. 2024;118(2):137-4.
65. Waware SY, Chougule SM, Yadav RS, Biradar R, Patil P, Munde KH, Kardekar NB, Nimbalkar AG, Kurhade AS, Murali G, Kore SS. A comprehensive evaluation of recent studies investigating nanofluids utilization in heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024;119(2):160-72.
66. Upadhe SN, Mhamane SC, Kurhade AS, Bapat PV, Dhavale DB, Kore LJ. Water saving and hygienic faucet for public places in developing countries. InTechno-Societal 2018: Proceedings of the 2nd International Conference on Advanced Technologies for Societal Applications-Volume 1 2020 (pp. 617-624). Springer International Publishing.
67. Sidhappa KA, Hande MS, Patil MS, Mask MV. Heat Transfer Enhancement by using Twisted Tape Inserts with circular holes in forced convection. International journal of innovations in engineering research and technology. 2016 Mar;3(3):1-7.
68. Kurhade AS, Kardekar NB, Bhambare PS, Waware SY, Yadav RS, Pawar P, Kirpekar S. A comprehensive review of electronic cooling technologies in harsh field environments: obstacles, progress, and prospects. J Mines Met Fuels. 2024; 72 (6): 557-79 [Internet].
69. Kurhade AS, Waware SY, Bhambare PS, Biradar R, Yadav RS, Patil VN. A comprehensive study on Calophyllum inophyllum biodiesel and dimethyl carbonate blends: Performance optimization and emission control in diesel engines. J Mines Met Fuels. 2024; 72 (5): 499-507.
70. Kurhade AS, Waware SY, Munde KH, Biradar R, Yadav RS, Patil P, Patil VN, Dalvi SA. Performance of solar collector using recycled aluminium cans for drying. J Mines Met Fuels. 2024; 72 (5): 455-61.
71. Kurhade AS, Siraskar GD, Bhambare PS, Dixit SM, Waware SY. Numerical investigation on the influence of substrate board thermal conductivity on electronic component temperature regulation. J Adv Res Numer Heat Trans. 2024;23(1):28-37.
72. Kurhade AS, Siraskar GD, Kondhalkar GE, Darade MM, Yadav RS, Biradar R, Waware SY, Charwad GA. Optimizing aerofoil design: A comprehensive analysis of aerodynamic efficiency through CFD simulations and wind tunnel experiments. Journal of Mines, Metals and Fuels. 2024 Sep 17:713-24.
73. Kurhade AS, Siraskar GD, Darade MM, Dhumal JR, Kardile CS, Biradar R, Patil SP, Waware SY. Predicting heat transfer enhancement with twisted tape inserts using fuzzy logic techniques in heat exchangers. Journal of Mines, Metals and Fuels. 2024 Sep 17:743-50.

74. Kurhade AS, Kadam AA, Biradar R, Bhambare PS, Gadekar T, Patil P, Yadav RS, Waware SY. Experimental investigation of heat transfer from symmetric and asymmetric IC Chips mounted on the SMPS board with and without PCM. J Adv Res Fluid Mech Therm Sc. 2024;121(1):137-4.
75. Patil P, Kardekar N, Yadav R, Kurhade A, Kamble D. Nanofluids: An Experimental Study for MQL Grinding. Journal of Mines, Metals and Fuels. 2023;71(12):2751-6.
76. Patil P, Kardekar N, Yadav R, Kurhade A, Kamble D. Al2O3 nanofluids: An experimental study for MQL grinding. J Mines Met Fuels. 2023; 2751-6.
77. Kurhade AS, Bhambare PS, Desai VP, Murali G, Yadav RS, Patil P, Gadekar T, Biradar R, Kirpekar S, Charwad GA, Waware SY. Investigating the effect of heat transfer influenced by applying wavy corrugated twisted tape inserts in double pipe heat exchangers. J Adv Res Fluid Mech Therm Sc.[Internet]. 2024;122(2):146-55.
78. Kurhade AS, Murali G, Jadhav PA, Bhambare PS, Waware SY, Gadekar T, Yadav RS, Biradar R, Patil P. Performance analysis of corrugated twisted tape inserts for heat transfer augmentation. J Adv Res Fluid Mech Therm Sci. 2024;121(2):192-200.
79. Kurhade MA, Dange MM, Nalawade DB. Effect of wavy (Corrugated) twisted tape inserts on heat transfer in a double pipe heat exchanger. International journal of innovations in engineering research and technology. 2015;2(1):1-8.
80. Kurhade AS, Gadekar T, Siraskar GD, Jawalkar SS, Biradar R, Kadam AA, Yadav RS, Dalvi SA, Waware SY, Mali CN. Thermal Performance Analysis of Electronic Components on Different Substrate Materials. Journal of Mines, Metals and Fuels. 2024 Oct 30:1093-8.
81. Kurhade AS, Siraskar GD, Jawalkar SS, Gadekar T, Bhambare PS, Biradar R, Yadav RS, Waware SY, Mali CN. The impact of circular holes in twisted tape inserts on forced convection heat transfer. J Mines Met Fuels. 2024; 72 (9): 1005–12 [Internet].
82. Kurhade AS, Darade MM, Siraskar GD, Biradar R, Mahajan RG, Kardile CS, Waware SY, Yadav RS. State-of-the-Art Cooling Solutions for Electronic Devices Operating in Harsh Conditions. Journal of Mines, Metals and Fuels. 2024 Sep 27:843-61.
83. Kurhade AS, Warke P, Maniyar K, Bhambare PS, Waware SY, Deshpande S, Harsur S, Ingle M, Kolhe P, Patil PA, Jadhav P. The wind rose analysis of temperature variation with sensor implantation technique for a wind turbine. J Adv Res Fluid Mech Therm Sci. 2024;122(1):1-8.
84. Kurhade AS, Siraskar GD, Bhambare PS, Keloth D, Kaithari SM, Waware SY. Enhancing Smartphone Circuit Cooling: A Computational Study of PCM Integration. J. Adv. Res. Numer. Heat Trans. 2024 Nov 30;27(1):132-45.
85. Yadav RS, Gadekar T, Gundage V, Patil P, Patil A, Patil P, Patil A, Sutar R, Kurhade AS. Numerical and Experimental Investigation of the Effect of Overlapping Angle on Strength and Deformation of Curved Plate Joined Using Arc Welding Process. Journal of Mines, Metals and Fuels. 2024 Oct 30:1059-66.
86. Yadav RS, Nimbalkar A, Gadekar T, Patil P, Patil VN, Gholap AB, Kurhade AS, Dhumal JR, Waware SY. Comparison of Experimental and Numerical Investigation of Mono-Composite and Metal Leaf Spring. Journal of Mines, Metals and Fuels. 2024 Sep 27:815-27.
87. Deshpande SV, Pawar RS, Keche AJ, Kurhade A. Absolute time surface finish measurement of stepped holding shaft by automatic system. Journal of Advanced Manufacturing Systems. 2025 Jan 17.
88. Kurhade AS, Siraskar GD, Bhambare PS, Murali G, Deshpande SV, Warke PS, Waware SY. Simulation and Analysis of Heat Transfer in Counter-Flow Helical Double-Pipe Heat Exchangers Using CFD. International Journal of Modern Physics C. 2025 Jan 10.
89. Parkar A, Yadav RS, Chopade R, Dhavase N, Dhumal JR, Mankar SP, Patil S, Ghuge K, Giri B, Kurhade AS. Automating the Two-Dimensional Design of Heating, Ventilation, Air Conditioning, and Refrigeration (HVACR) Ducts using Computer Programming Language: An Algorithmic Approach. Journal of Mines, Metals and Fuels. 2025 Jan 7:211-20.
90. Kurhade AS, Siraskar GD, Darade MM, Murali G, Katkar TR, Patil SP, Charwad GA, Waware SY, Yadav RS. Enhancement in Heat Transfer with Nanofluids in Double-Pipe Heat Exchangers. Journal of Mines, Metals and Fuels. 2025 Jan 7:165-72.
91. Kurhade AS, Chougule SM, Kharat PV, Kondhalkar GE, Murali G, Raut PN, Charwad GA, Waware SY, Yadav RS. Integrated Approach to Enhance Vehicle Safety: A Novel Bumper Design with Energy-Absorbing Mechanisms. Journal of Mines, Metals and Fuels. 2025 Jan 7:27-35.
92. Raut PN, Dolas AS, Chougule SM, Darade MM, Murali G, Waware SY, Kurhade AS. Green Adsorbents for Heavy Metal Removal: A Study on Zinc Ion Uptake by Tinospora cordifolia Biocarbon. Journal of Mines, Metals and Fuels. 2025 Jan 7:21-5.
93. Yadav R, Nimbalkar A, Kirpekar S, Patil PJ, Dalvi SA, Jadhav PA, Kurhade AS, Wakchaure GN. Effect of Transformed-Induced Plasticity Steel Plate Thickness on Ultimate Tensile Strength of Butt Welded Joint using Nd: YAG Laser. International Journal of Vehicle Structures and Systems. 2024 Dec 31;16(6).
94. Yadav RS, Gandhi P, Veeranjaneyulu K, Gaji R, Kirpekar S, Pawar D, Khairnar YS, Patil S, Kurhade AS, Patil SP. Influence of Plate Thickness on the Mechanical Behaviour of Mild Steel Curved Plates: An Experimental Study. Journal of Mines, Metals and Fuels. 2024 Dec 11:1319-27.
95. Kurhade AS, Bhambare PS, Siraskar GD, Mukesh S, Dixit PS, Waware SY. Computational Study on Thermal Management of IC Chips with Phase Change Materials.

96. Kurhade MA, Dange MM, Nalawade DB. Fuzzy Logic Modeling of Heat Transfer in a Double Pipe Heat Exchanger with Wavy (Corrugated) Twisted Tape Inserts. International Journal of Innovations in Engineering Research and Technology.;2(1):1-8.
97. Kurhade AS, Siraskar GD, Raut PN, Dolas AS, Murali G, Dalvi SA, Waware SY, Yadav RS. Investigating the Impact of Oxygenated Additives on Exhaust Emissions from Unleaded Gasoline Vehicles. jmmf. 2025 Feb. 24;73(2):333-44
98. Purandare P, Yadav RS, Nema AA, Kulkarni A, Kirpekar S, Giri B, Patil PA, Jagdale M, Kurhade AS. Comparative Study of Helical Coil, Spiral Coil and Conical Coil (90O) Heat Exchanger for Single Phase Fluid Flow. jmmf. 2025 Feb. 24 ;73(2):377-84.
99. Kurhade AS, Siraskar GD, Dalvi SA, Kharat PV, Jadhav NA, Shelkande VD, Murali G, Waware SY, Yadav RS. Passive Cooling of EV Batteries Using Phase Change Material: A Simulation Study. jmmf . 2025 Feb. 24 ;73(2):447-54.
100. Kurhade AS, Kharat PV, Chougule SM, Darade MM, Karad MM, Murali G, Charwad GA, Waware SY, Yadav RS. Harnessing the Power of Plastic Waste: A Sustainable Approach to Fuel Production. jmmf . 2025 Feb. 24;73(2):467-73.
101. Kurhade AS, Siraskar GD, Deshmukh MT, Patil PA, Chaudhari SS, Kadam AA, Dolas AS, Mahajan RG, Waware SY, Yadav RS. Impact of PCM on Heat Dissipation from IC Chips. Journal of Mines, Metals & Fuels. 2025 Mar 1;73(3).
102. Ramani P, Reji V, Sathish Kumar V, Murali G, Kurhade AS. Deep Learning-Based Detection and Classification of Moss and Crack Damage in Rock Structures for Geo-Mechanical Preservation. Journal of Mines, Metals & Fuels. 2025 Mar 1;73(3).
103. Chippalkatti S, Chekuri RB, Ohol SS, Shinde NM, Barmavatu P, Shelkande VD, Murali G, Kurhade AS. Enhancing Heat Transfer in Micro-Channel Heat Sinks through Geometrical Optimization. Journal of Mines, Metals & Fuels. 2025 Mar 1;73(3).
104. Kurhade AS, Siraskar GD, Chekuri RB, Murali G, Pawar P, Patil AR, Waware SY, Yadav RS. Biodiesel Blends: A Sustainable Solution for Diesel Engine Performance Improvement. Journal of Mines, Metals & Fuels. 2025 Mar 1;73(3).
105. Kurhade AS, Bhavani P, Patil SA, Kolhalkar NR, Chalapathi KS, Patil PA, Waware SY. Mitigating Environmental Impact: A Study on the Performance and Emissions of a Diesel Engine Fueled with Biodiesel Blend. jmmf [Internet]. 2025 Apr. 16 [cited 2025 Apr. 28];73(4):981-9.
106. Wakchaure GN, Vijayarao P, Jadhav TA, Bhamare YM, Jagtap A, Gaji R, Chavan Patil AS, Kamble SD, Jagtap SV, Yadav RS, Kurhade AS. Performance Evaluation of Trapezoidal Ducts with Delta Wing Vortex Generators: An Experimental Investigation. jmmf [Internet]. 2025 Apr. 16 [cited 2025 Apr. 28];73(4):991-1003.
107. Wakchaure GN, Jagtap SV, Gandhi P, Chavan Patil AS, Kandharkar S, Kokare NN, Bhamare YM, Kamble SD, Jadhav A, Yadav RS, Kurhade AS. Heat Transfer Characteristics of Trapezoidal Duct using Delta Wing Vortex Generators. jmmf [Internet]. 2025 Apr. 17 [cited 2025 Apr. 28];73(4):1053-6.
108. Chougule SM, Murali G, Kurhade AS. Failure Investigation of the Driving Shaft in an Industrial Paddle Mixer. jmmf [Internet]. 2025 May 9 [cited 2025 May 12];73(5):1247-56.
109. Kurhade AS, Sugumaran S, Kolhalkar NR, Karad MM, Mahajan RG, Shinde NM, Dalvi SA, Waware SY. Thermal Management of Mobile Devices <i>via</i> PCM. jmmf [Internet]. 2025 May 9 [cited 2025 May 12];73(5):1313-20.
110. Chougule SM, Murali G, Kurhade AS. Finite Element Analysis and Design Optimization of a Paddle Mixer Shaft. jmmf [Internet]. 2025 May 9 [cited 2025 May 12];73(5):1343-54.
111. Waware SY, Ahire PP, Napate K, Biradar R, Patil SP, Kore SS, Kurhade AS. Advancements in Heat Transfer Enhancement using Perforated Twisted Tapes: A Comprehensive Review. jmmf [Internet]. 2025 May 9 [cited 2025 May 12];73(5):1355-63.
112. Patil Y, Tatiya M, Dharmadhikari DD, Shahakar M, Patil SK, Mahajan RG, Kurhade AS. The Role of AI in Reducing Environmental Impact in the Mining Sector. jmmf [Internet]. 2025 May 9 [cited 2025 May 12];73(5):1365-78.
113. Chougule SM, Murali G, Kurhade AS. Dynamic simulation and performance evaluation of vibratory bowl feeders integrated with paddle shaft mechanisms. Advances in Science and Technology Research Journal. 2025;19(7):179-96.
114. Rao SS, Sugumaran S, Ameresh H, Amruth E, Thamke VP, Waware SY, Patil PA, Kurhade AS. Impact of Regularly Spaced Cut Sections on the Heat Transfer Efficiency of Helical Strip Inserts in Circular Pipes. jmmf [Internet]. 2025 Jun. 4 [cited 2025 Jun. 6];73(6):1517-25
115. Sanadi A, Shinde S, Burgute G, Purandare P, Ramtirthkar C, Jadhav Sachin Z, Awati SS, Yadav R, Kurhade A. Assessing the Impact of Exhaust Gas Recirculation on the Emission Profile of a Diesel Engine Operating on Mohua Oil: An Experimental Study. jmmf [Internet]. 2025 Jun. 4 [cited 2025 Jun. 6];73(6):1535-42.
116. Chaudhari SS, Shahakar M, Gholap P, Dhamdhere PB, Agrawal SS, Mahajan RG, Kurhade AS, Waware SY. Enhancing Energy Efficiency in Metallurgical Operations Using AI: A State of the Art Review. jmmf [Internet]. 2025 Jun. 4 [cited 2025 Jun. 6];73(6):1595-616.

117. Waware SY, Ahire PP, Ghutepatil PR, Biradar R, Kadam AA, Kore SS, Kurhade AS, Ghunake KB. Enhancing Heat Transfer in Tubular Heat Exchanger Using Minijet Technology. jmmf [Internet]. 2025 Jun. 4 [cited 2025 Jun. 6];73(6):1699-706.
118. Chougule SM, Murali G, Kurhade AS. Design and Analysis of Industrial Material Handling Systems using FEA and Dynamic Simulation Techniques: FEA AND SIMULATION-BASED DESIGN OF MATERIAL HANDLING SYSTEMS. Journal of Scientific & Industrial Research (JSIR). 2025 Jun 18;84(6):645-53.