Journal of Manufacturing Systems 78 (2025) 153–177

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Review

Leveraging AI for energy-efficient manufacturing systems: Review and future prospectives

Mohammad Mehdi Keramati Feyz Abadi, Chao Liu *, Ming Zhang, Youxi Hu, Yuchun Xu

College of Engineering and Physical Sciences, Aston University, B4 7ET Birmingham, UK

ARTICLE INFO

Keywords:
Manufacturing system
Energy efficiency
Digital twin
Artificial Intelligence
Machine learning
Reinforcement learning

ABSTRACT

Energy poses a significant challenge in the industrial sector, and the abundance of data generated by Industry 4.0 technologies offers the opportunity to leverage Artificial Intelligence (AI) for enhancing energy efficiency (EE) in manufacturing processes, particularly within manufacturing systems. However, fully realizing AI's potential in addressing energy challenges requires a comprehensive review of AI methodologies aimed at overcoming obstacles in energy-efficient manufacturing systems. This article provides a systematic review that combines both quantitative and qualitative analyses of literature from the past ten years, focusing on mitigating prevalent energy efficiency challenges in manufacturing systems through AI-related methodologies. These challenges include Monitoring and Prediction, Real-Time Control, Scheduling, and Parameters Optimization. The AI-related solutions proposed in the reviewed research articles utilize Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) techniques, either individually or in combination with other methods. A total of 67 journal papers on manufacturing systems, addressing the mentioned energy challenges through AI-related approaches, have been identified and thoroughly reviewed. As a result of this review, an Energy Efficient-Digital Twin (EE-DT) framework is proposed, demonstrating how a DT, equipped with AI techniques, can be applied to solve energy issues in manufacturing systems. This study provides scholars with a comprehensive guideline for selecting various types of AI methods to address common challenges in energy-efficient manufacturing systems, while also highlighting some promising future research directions.

1. Introduction

As a result of global economy expansion and population growth, the energy demand increased sharply by almost 36 % between 2000 and 2018 [1] and it is projected that to grow by roughly 1.3 % annually up to 2040 with the same policies and subsequent usage pace [2]. The industrial sector accounts for more than 30 % of global energy consumption, contributing substantially to environmental impacts, including CO_2 emissions and the depletion of renewable and non-renewable resources. Additionally, rising energy prices are increasing production costs, further intensifying the need for energy-efficient systems within the industry [3–5].

In response, many countries have implemented various initiatives, known as Industrial Energy Efficiency Programs [6]. For instance, Industrial energy efficiency objectives are a critical component of the United Kingdom's strategy to achieve its 2050 Net Zero targets [7–9]. These objectives are also integral to the Energy Star Program in the United States [10,11], the European Union's 2030 Climate and Energy Policy Framework [12,13] and China's 14th Five-Year Plan for National Economic and Social Development [14].

Abbreviations: AC, Actor- Critic; AGV, Automated Guided Vehicle; AI, Artificial Intelligence; ANN, Artificial Neural Network; CNN, Convolutional Neural Network; CNC, Computer Numerical Control; CRITIC, Criteria Importance Through Intercriteria Correlation; DL, Deep Learning; DT, Digital Twin; DQN, Deep Q-Network; DRL, Deep Reinforcement Learning; FCM, Fuzzy C-Means; GA, Genetic Algorithm; GCN, Graph Convolutional Network; GRU, Gated Recurrent Unit; GPR, Gaussian Process Regression; HMI, Human Machine Interface; KDE, Kernel Density Estimation; KNN, K-Nearest Neighbors; LINMAP, Linear Programming Techniques for Multidimensional Analysis of Preference; LSTM, Long -Short Term Memory; ML, Machine Learning; MLE, Maximum Likelihood Estimation; MLP, Muli-layer perceptions; NN, Neural Network; NSGA-II, Non-dominated Sorting Genetic Algorithm II; PPO, Proximal Policy Optimization; PSO, Particle Swarm Optimization; QL, Q-Learning; RF, Random Forest; RL, Reinforcement Learning; RTP, Real-Time Price; RuLSIF, Relative Unconstrained Least-Squares Importance Fitting; SLR, Systematic Literature Review; SVR, Support Vector Regression; TBRFFNN, Taguchi-based Bayesian Regularized Feed-ForwardNeural Network; YOLO, You Look Only Once.

* Corresponding author.
E-mail address: c.liu16@aston.ac.uk (C. Liu).

https://doi.org/10.1016/j.jmsy.2024.11.017
Received 16 July 2024; Received in revised form 3 November 2024; Accepted 23 November 2024
Available online 29 November 2024

To enhance energy efficiency in the industrial sector, Industry 4.0 digital technologies offer the opportunity to record and explore data potentials. Emerging technologies, such as the Industrial Internet of Things, facilitate extensive data collection across various operational processes. Concurrently, advancements in AI enable comprehensive big data analysis and support data-driven decision-making.

AI applications in manufacturing significantly enhance efficiency, quality, and sustainability by effectively managing complex, nonlinear systems and adapting to diverse process variables. AI approaches —including ML, DL, and RL, either independently or in combination with other algorithms— are widely applied across various manufacturing domains: in intelligent welding and friction stir welding, ML optimizes parameters and predicts joint properties, improving real-time control and reducing defects [15,16]. In metal forming, ML aids in adjusting critical parameters like force and temperature to ensure quality and minimize waste [17]. For milling advanced composites, ML models predict surface characteristics to achieve high-quality finishes [18], and in laser cutting, ML enables precise control for efficient material use [19]. Eco-friendly machining methods, such as Minimum Quantity Lubrication, also benefit from ML predictions that optimize surface quality and tool wear [20]. These applications demonstrate the critical role of AI-driven ML models in optimizing decision-making and enhancing manufacturing processes across diverse fields.

Additionally, DT technology allows for dynamic interaction between AI models (virtual side) and physical entities, enhancing monitoring and control capabilities. This paradigm shift from traditional, knowledge-based solutions to sophisticated, AI-driven methodologies is fundamentally reshaping manufacturing process toward objectives, such as energy efficiency [21–23].

Fully realizing AI's potential in addressing energy inefficiencies requires a comprehensive review of AI methodologies aimed at overcoming obstacles in energy-efficient manufacturing systems. To this end, this article presents a systematic review of the frequent energy related challenges focusing on manufacturing systems, which are tackled by AI-based or aided solutions, by examining the relevant published research to date. The remainder of the SLR is structured as follows in five sections. The research methodology of this paper is presented in Section 2. In Section 3, a bibliometric analysis of research on AI for energy-efficient manufacturing systems over the last decade is provided to investigate research trends and focus. Section 4 discusses the issues related to energy-efficient manufacturing systems comprehensively and examines the proposed AI-related solutions for each energy efficiency challenge in detail. In Section 5, a conceptual EE-DT framework is presented, featuring a DT equipped with AI techniques to enhance energy efficiency in manufacturing systems. Section 6 presents the identified research challenges. Finally, Section 7 concludes the paper with a summary.

2. Review methodology

A literature review is a critical component of any scientific contribution. It encompasses the motivations behind the research, an assessment of state-of-the-art technologies, recent advancements, emerging trends, and identified limitations within a specific research domain, while being thorough, unbiased, reproducible, and comprehensive, citing pertinent existing literature. To ensure rigor and standardization in this SLR, we followed the guidelines proposed by [24]. The first step in this process involves defining the research questions for the literature review as follows:

Question 1: Which existing literature reviews have addressed AI for energy-efficient manufacturing systems, and which AI-related methods have these reviews considered?

Question 2: What are the trends and focuses of research on AI for energy-efficient manufacturing systems over the last decade?

Question 3: What are the common energy efficiency issues in manufacturing systems?

Question 4: How do AI algorithms contribute to solving energy-related problems in manufacturing systems?

Question 5. What are the major research issues and challenges associated with AI approaches for energy-efficient manufacturing systems?

Each of these research questions is addressed in the corresponding sections, as illustrated in Fig. 1.

The focused aspects of this article are twofold: 1) energy challenges of manufacturing systems and 2) the proposed solutions, encompassing utilization of AI subfields, independently or in combination with other algorithms for tackling the mentioned challenges. The literature search is conducted using Scopus, concentrating on titles, abstracts and author keywords. Among all available types of documents in Scopus, the analysis includes only journal articles and reviews written in English. This strategy helps in deriving quality publications and proposing more reliable analyses.

The analysis covers the period from early 2013, when the first relevant paper related to the scope of this study—encompassing manufacturing systems, energy, and AI—was published, to late February 2024, when the most recent paper in this area was published.

The chosen keywords can be grouped together into three categories: Domain, indicating the focused aspect of manufacturing; Objective, specifying the targeted challenge; and the Solution implies on the targeted solutions. The keywords of the categories are as the following:

1. Domain: "manufacturing system* ", "production system* ", "machining system* ", "machining process", "cyber-physical production system* ".
2. Objective: "energy efficiency", "energy-efficient* ", "energy-saving", "energy-aware* ", "energy-conscious* ", "low carbon* ", "sustainable manufacturing", "energy monitoring", "energy management", "energy optimization* ".
3. Solution: "neural network* ", "supervised learning", "unsupervised learning", "reinforcement learning", "machine learning", "clustering", "classification", "artificial intelligence* ".

Using the paper selection procedure demonstrated in Fig. 2, we have identified 67 papers, including 3 literature reviews relevant to our scope. Based on the review of the identified papers, it was observed that the existing literature can be grouped into four main categories. The first category includes papers that emphasize the importance of Monitoring and Prediction as a foundation for energy-efficient decision-making. The other three categories focus on specific energy-efficient decision-making approaches: Real-Time Control, Scheduling, and Parameters Optimization. These categories represent what we refer to as energy efficiency challenges in manufacturing systems. Specifically, these challenges are recurring areas where both research and industry aim to make improvements to enhance energy efficiency. Addressing these four challenges is crucial for optimizing energy use in manufacturing systems.

It is important to clarify that in this context, an energy-efficient manufacturing system refers to a system that consumes energy in an optimized, efficient manner. Efficient energy usage does not always imply a reduction in overall energy consumption. For example, a system may maintain the same level of energy consumption and productivity while reducing time inefficiencies, thereby improving energy efficiency without directly decreasing energy consumption. The goal is to use energy more effectively, minimizing waste and maximizing output relative to the energy consumed. Thus, enhancing energy efficiency in manufacturing systems involves addressing four key challenges: (1) **Monitoring and Prediction**, (2) **Real-Time Control**, (3) **Scheduling**, and (4) **Parameters Optimization**. These categories reflect the critical areas that need to be addressed to achieve energy-efficient manufacturing. As such, the reviewed papers have been classified into these four categories.

Moreover, we have identified two review articles closely related to our work. In Table 1, we present a comparison between these articles and the existing literature in terms of the variety of AI-related solutions

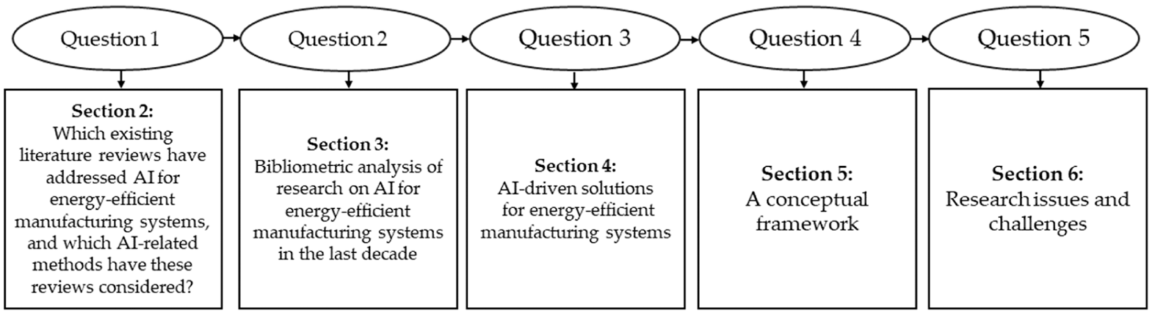

Fig. 1. Research questions and the structure of this paper.

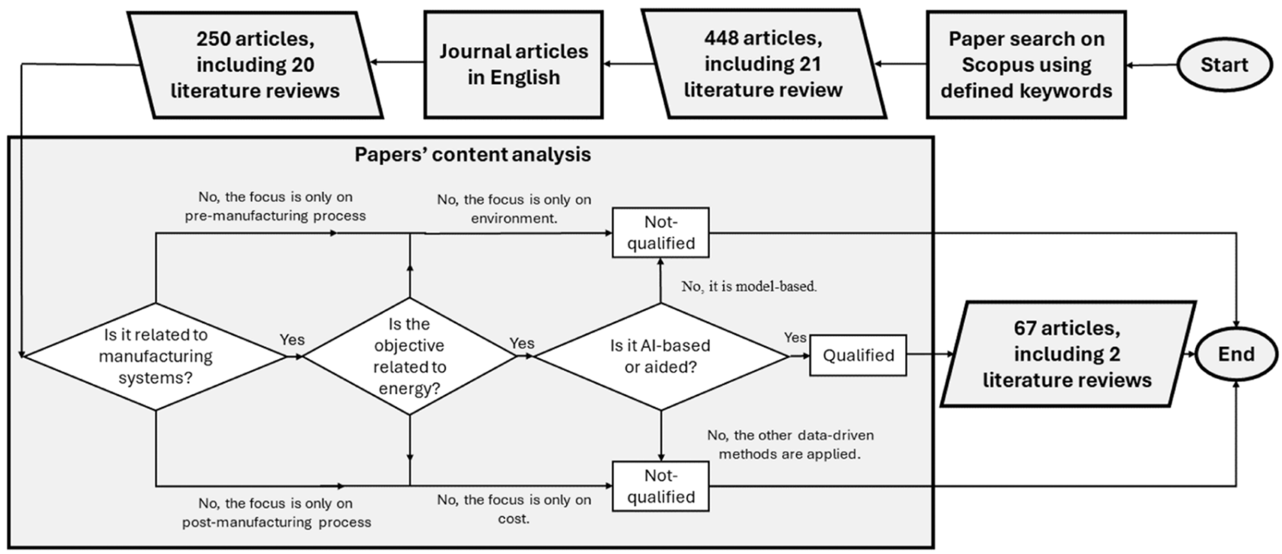

Fig. 2. Paper selection procedure.

Table 1
Comparison with other energy efficiency review papers.

Literature	ML	DL	RL	DRL	Combination of AI branches	Combination of AI branches with other algorithms
[14]	✔	✔	✔	-	-	-
[15]	✔	✔	-	-	-	-
This paper	✔	✔	✔	✔	✔	✔

considered. To facilitate this comparison, we employ a classification based on four key AI branches: ML (referring to classical ML algorithms), DL, RL, and DRL. Each of these branches represents a distinct approach to AI, with significant differences in their methodologies and applications.

- ML refers to classical ML algorithms, which include techniques such as decision trees, support vector machines, and linear regression. These methods are effective for structured data analysis and are often used in applications like classification and regression. However, they may struggle with unstructured data or complex feature representations that require more advanced modeling.
- DL is a specialized subset of ML that uses neural networks with many layers (i.e., deep architectures). DL excels at modeling complex, unstructured data such as images, speech, and text, where classical ML methods typically fall short. DL has been a major driver of recent AI advancements, particularly in tasks requiring high-dimensional feature extraction.
- RL differs from classical ML and DL by focusing on sequential decision-making processes. An agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. RL is particularly effective for tasks that require a sequence of decisions, such as autonomous systems.
- DRL combines RL with DL techniques, enabling agents to learn from high-dimensional inputs using deep neural networks. DRL has become increasingly important in solving complex tasks, such as autonomous control, where traditional RL or classical ML methods are insufficient.

The distinction between these branches is important due to their varying strengths and limitations. Earlier reviews, up until 2022, primarily focused on ML (classical), DL, and RL, but largely excluded DRL. In contrast, this paper includes DRL and explores additional AI-driven solutions by considering hybrid approaches, such as combining the main branches with each other or with other algorithms. This broader scope extends the analysis to literature published up until 2024, reflecting the evolving landscape of AI.

In addition to this classification for comparing our review with existing literature, we use a second classification to structure the literature review conducted in this paper. This classification distinguishes ML (classical algorithms), Shallow NN, DL, and RL. In this context, RL includes DRL as part of its scope. We also introduce shallow NNs, which refer to neural networks with simpler architectures—typically one or two hidden layers and a limited number of neurons. Shallow NNs differ from the more complex architectures of DL, and their frequent application in less complex tasks makes them an important addition to this classification. Thus, the first classification (ML [classical], DL, RL, DRL) is used to compare our work with existing reviews, while the second classification (ML [classical], NN, DL, RL) is used to organize the literature review, with RL encompassing DRL. These distinctions allow for a more detailed and comprehensive exploration of AI-driven solutions in the literature, while clarifying the different methodologies being applied.

3. Bibliometric analysis of research on AI and energy-efficient manufacturing systems in the last decade

In this section, a bibliometric analysis is conducted using data gathered from Scopus to investigate research trends and focuses on AI and energy-efficient manufacturing systems over the past decade.

3.1. Annual trend analysis

The publication trend analysis is an important factor, indicating the focused researchers' interests and efforts over the years. Fig. 3 represents a year-wise publication trend in AI and energy-efficient manufacturing systems. The first article proposing AI as a solution to improve energy efficiency in manufacturing systems was published in 2013. Over the last 10 years, a total of 65 papers have been published.

Generally, it is evident that studies in this field are increasing. Specifically, there is a gradual increase from 2018 to 2020 and a sharp rise in publications from 2020, peaking in 2023. It is worth mentioning that, because only the publications in the first three months of 2024 are reviewed in this study, 2024 is not considered in the trend analysis.

Another analysis relates to trends in addressing various identified energy efficiency challenges in manufacturing systems, including Monitoring and Prediction, Real-Time Control, Scheduling, and Parameters Optimization using AI. As shown in Fig. 4, the bar chart reveals that studies on Scheduling and Parameters Optimization have been gradually increasing. In 2023, these two categories hold the first and second positions in the number of publications, respectively. While Real-Time Control was almost neglected in 2022, it gained attention again in 2023. This contrasts with Monitoring and Prediction, which received the least attention in 2023, despite being the most focused category in 2022. It can be concluded that the research focus within the scope of AI for energy efficiency in manufacturing systems has shifted from solely focusing on data analysis to data-driven decision making.

In addition to these, the trend in the utilization of different AI branches to address the mentioned issues is depicted in Fig. 5. In this figure, the bar chart demonstrates a growing trend in the utilization of advanced AI approaches, specifically RL and DL. It is worth mentioning that, among the different RL approaches, DRL captured more attention. Based on growing trends in Figs. 4 and 5, it can be concluded that the number of publications utilizing advanced AI algorithms, such as DRL, to solve Scheduling, Real-Time Control, and Parameters Optimization will increase in the upcoming years.

It is also important to assess the extent to which AI is becoming acceptable and reliable as the primary solution in manufacturing systems research. Fig. 6 illustrates the trend in AI utilization as the main solution, which has been clearly increasing, particularly between 2020 and 2023. In 2023, 12 papers recommended AI as the main solution, representing 75 % of the published papers that year. This surge in the utilization of AI as the main solution highlights increasing confidence in AI technologies for optimization within manufacturing systems.

3.2. Descriptive analysis

While the trend analysis in the previous section provides insights into research focuses over the last decade, the objective of this section is to investigate the identified energy efficiency challenges from the perspective of the proposed AI-driven solutions in the literature. The first analysis, depicted in Fig. 7, demonstrates the distribution of utilization of AI branches as the main solution or support for the main solution in addressing energy efficiency challenges. Generally, it can be derived from the picture that the highest percentage of utilization of AI as the main solution belongs to Monitoring and Prediction, while Parameters Optimization has the lowest. Real-Time Control and Scheduling hold the second and third ranks, respectively, in the utilization of AI-based solutions.

To be more specific with the utilized branches, RL is the most frequently applied approach, typically used as the main solution to solve energy-efficient challenges in manufacturing systems. It is the primary approach utilized for addressing Scheduling and Real-Time Control issues, and it is the second most used method in Parameters Optimization. It is important to note that RL is not applied to Monitoring and Prediction challenges because it is more suitable for optimization and decision-making problems rather than data analysis. Additionally, while the distribution of RL utilization in Scheduling is higher than in Real- Time Control, it is more often applied in Real-Time Control as the main decision maker.

Shallow NNs architectures are the second most frequently applied approaches, and Deep NNs and classical ML algorithms equally rank third. They are widely applied to support the main solution in decision-making-related challenges, including Scheduling, Real-Time Control, and Parameters Optimization, and are exclusively utilized as the main solution in Monitoring and Prediction. While it might be expected that RL would be the primary approach for Parameters Optimization, shallow NNs in combination with non-AI-related optimization methods or individually are more commonly applied.

There are two possible reasons for this: 1) due to the lower

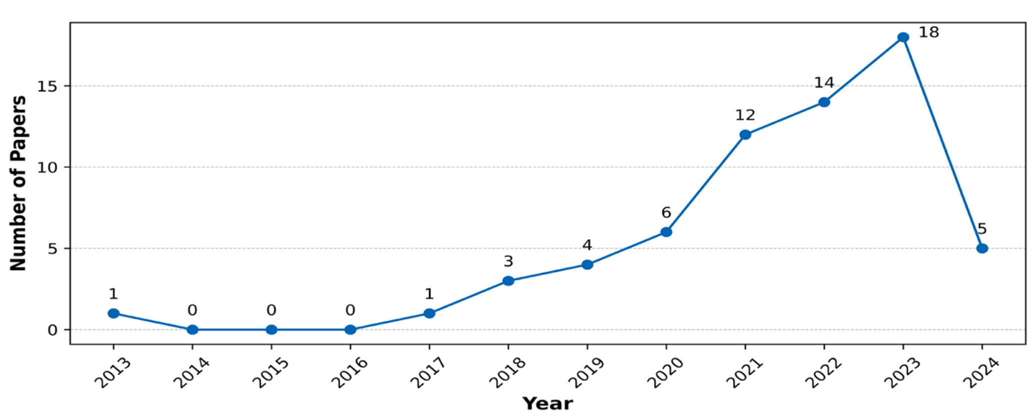

Fig. 3. Publication trends in the utilization of AI for energy-efficient manufacturing systems.

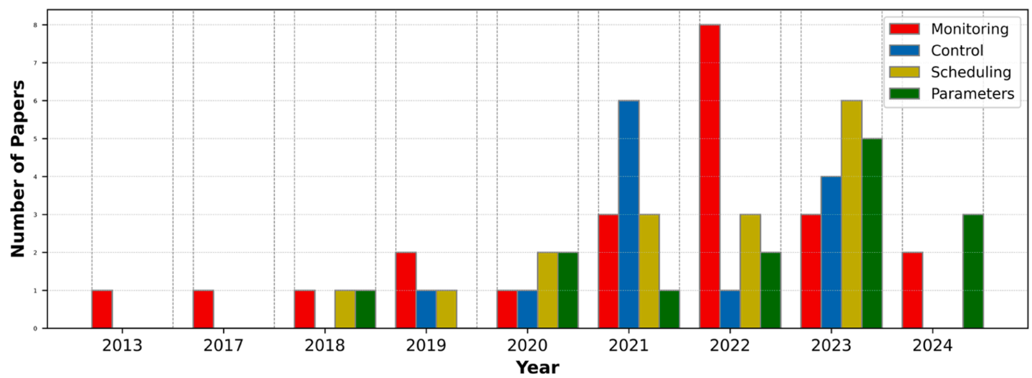

Fig. 4. Trends in addressing different energy efficiency challenges in Manufacturing Systems using AI.

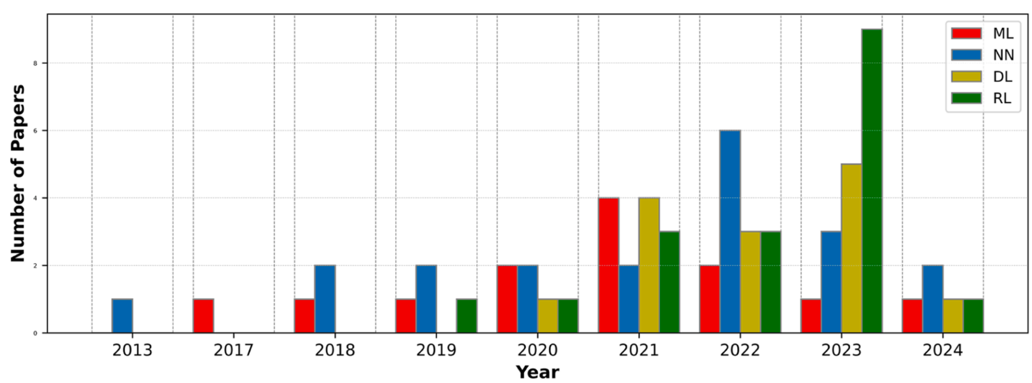

Fig. 5. Trends in utilization of different AI branches for energy-efficient manufacturing systems.

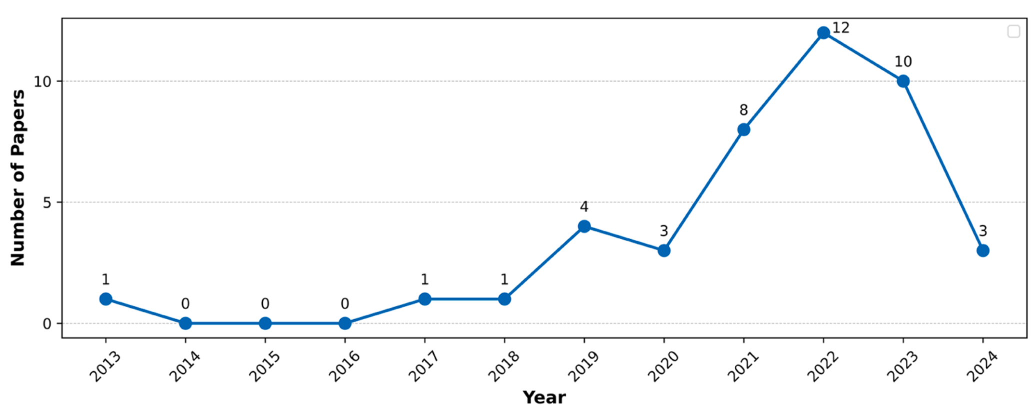

Fig. 6. Trend in utilization of AI as the main solution.

complexity of some problems, RL may not be the most cost-effective solution; 2) scholars have not yet paid enough attention to RL-related solutions, with only two published papers in this area in 2023 and 2024. For similar reasons, utilization of non-AI control solutions, supported by ML approaches in Real-Time Control challenge have a close distribution to RL-based solution.

In the second analysis, depicted in Fig. 8, the objective is to understand the extent to which the proposed AI solutions are validated in the real world. The data shows that real-world validation is consistently the lowest across all challenges, highlighting a significant gap in practical application. In contrast, the utilization of experimental data is predominant in most challenges, except for Real-Time Control, where simulation-based validation has the highest value. It is also important to note that, among the proposed solutions for the scheduling challenge, none are validated using real-world data.

3.3. Keywords co-occurrence analysis

To investigate the research trends and focuses on the field of AI and energy-efficient manufacturing systems over the past ten years, a co-occurrence analysis of keywords is performed using VOS viewer, a widely utilized software tool for constructing and visualizing bibliometric networks. It is worth mentioning that the keywords used in this research were derived from the Scopus database. Additionally, data cleansing was conducted on this database, including the removal of meaningless keywords and the aggregation of different variations of the same keywords.

The commonly used keywords in publications related to AI and energy-efficient manufacturing Systems are presented in Table 2. This table lists the keywords that co-occurred five times or more from 2013 to 2024, ranked by their frequency. From the table, it can be inferred that

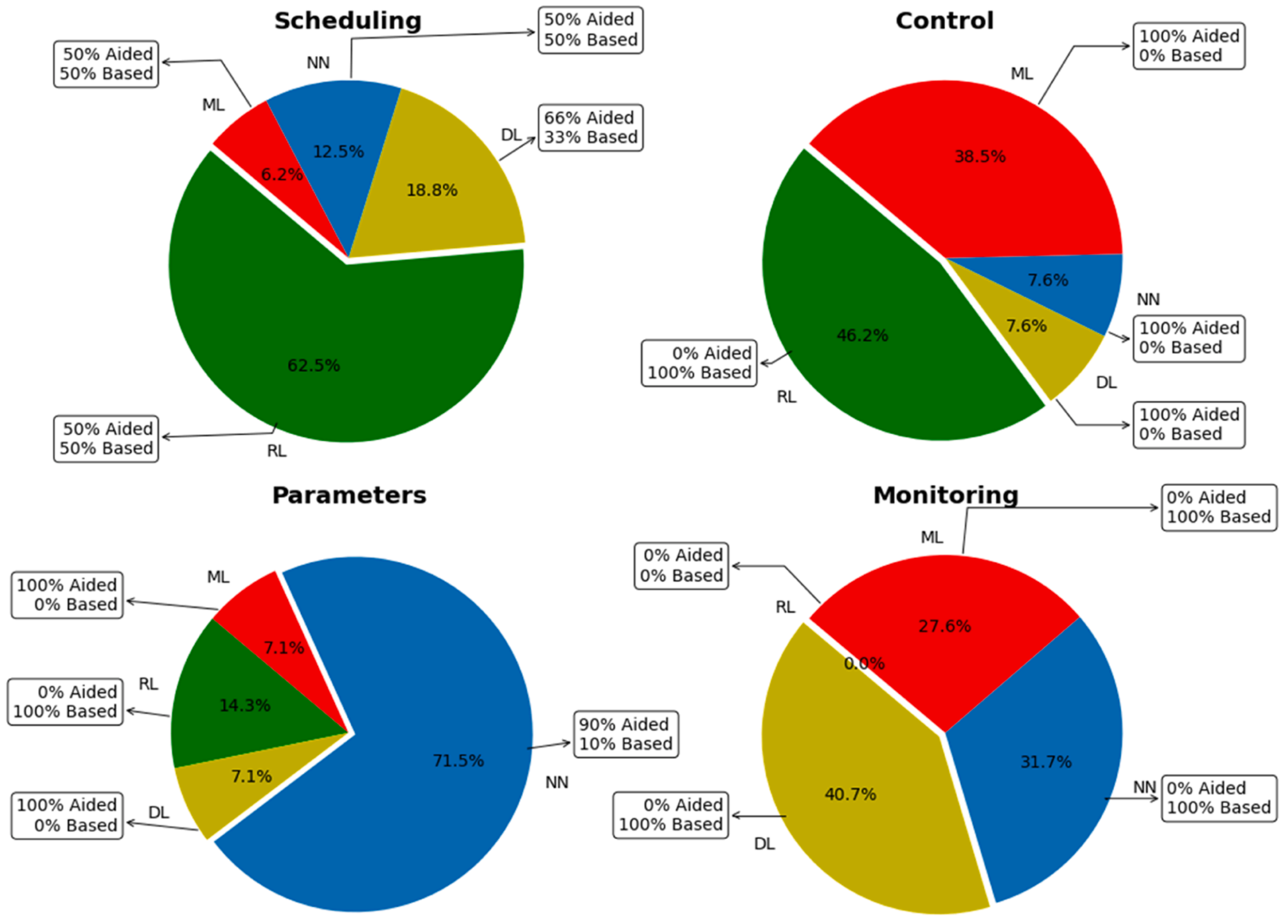

Fig. 7. Distribution of AI branch utilization, specifying the percentage of each branch used either as a based or aided solution for energy-efficiency challenges in manufacturing systems.

"Energy consumption", "Energy efficiency", "Machining" and "Reinforcement Learning" are the most frequently used keywords in these studies.

To gain a clearer understanding of the research focuses indicated by various keywords, Fig. 9 categorizes the keywords from Table 2 into three groups: Domain, Objective, and Solution. Within each group, the keywords are ranked based on their frequency in the publications. The Domain category pertains to the specific area of focus in manufacturing studies, with "Machining" holding the top rank in this category. The Objective category refers to the primary goal of the study, with "Energy consumption" being the highest-ranked objective. The Solution category includes keywords related to AI, with "Reinforcement Learning" and "Optimization" being the most frequently addressed topics in the papers.

The investigation of research keyword trends is the final keyword analysis in this section, enhancing our understanding of the research trends presented earlier. Fig. 10 depicts a temporal keyword co-occurrence network constructed from bibliometric data. The color gradient from purple to yellow represents the average publication year. The size of each node represents the frequency of the keyword, while the thickness of the link between two nodes indicates how often they co-occur. From the picture, it can be observed that there is a growing trend in the utilization of advanced AI approaches, progressing from shallow NNs architectures to DL approaches and continuing with RL, for addressing energy-relate objectives in manufacturing systems such as energy utilization optimization. The connections between these AI approaches and traditional manufacturing topics suggest a significant shift towards leveraging cutting-edge technologies to solve complex industrial challenges.

3.4. Transition from quantitative to qualitative

The quantitative bibliometric analysis presented in this section provides a thorough examination of research trends and focuses on AI-driven solutions for energy-efficient manufacturing systems. Some of the most important insights revealed by this analysis are as follows. Over the past decade, there has been a marked increase in the use of AI techniques to tackle energy efficiency challenges in manufacturing. Specifically, the analysis highlights a growing body of research centered on the utilization of AI as a primary solution, the implementation of advanced techniques such as RL and DL, and the application of AI-driven solutions in key areas like Scheduling and Parameters Optimization, where these technologies show significant potential for enhancing real-time decision-making. This growth aligns with a broader trend towards integrating AI for optimizing energy consumption in complex and dynamic manufacturing environments. Furthermore, the analysis indicates a shift in research priorities, transitioning from earlier studies focused on Monitoring and Prediction to more recent efforts emphasizing Real-Time Control, Scheduling, and Parameters Optimization. This evolution reflects a maturation in the field, moving beyond passive analysis of energy consumption toward active, real-time optimization of manufacturing processes using AI technologies.

However, the analysis also highlights a critical gap: while advanced AI techniques are widely studied, their practical validation and implementation in real-world manufacturing systems remain limited. This points to the need for further applied research and pilot studies to bridge the gap between theoretical advancements and practical applications. The quantitative analysis successfully identifies these key trends, and emerging research focuses but does not fully explore the specific energy

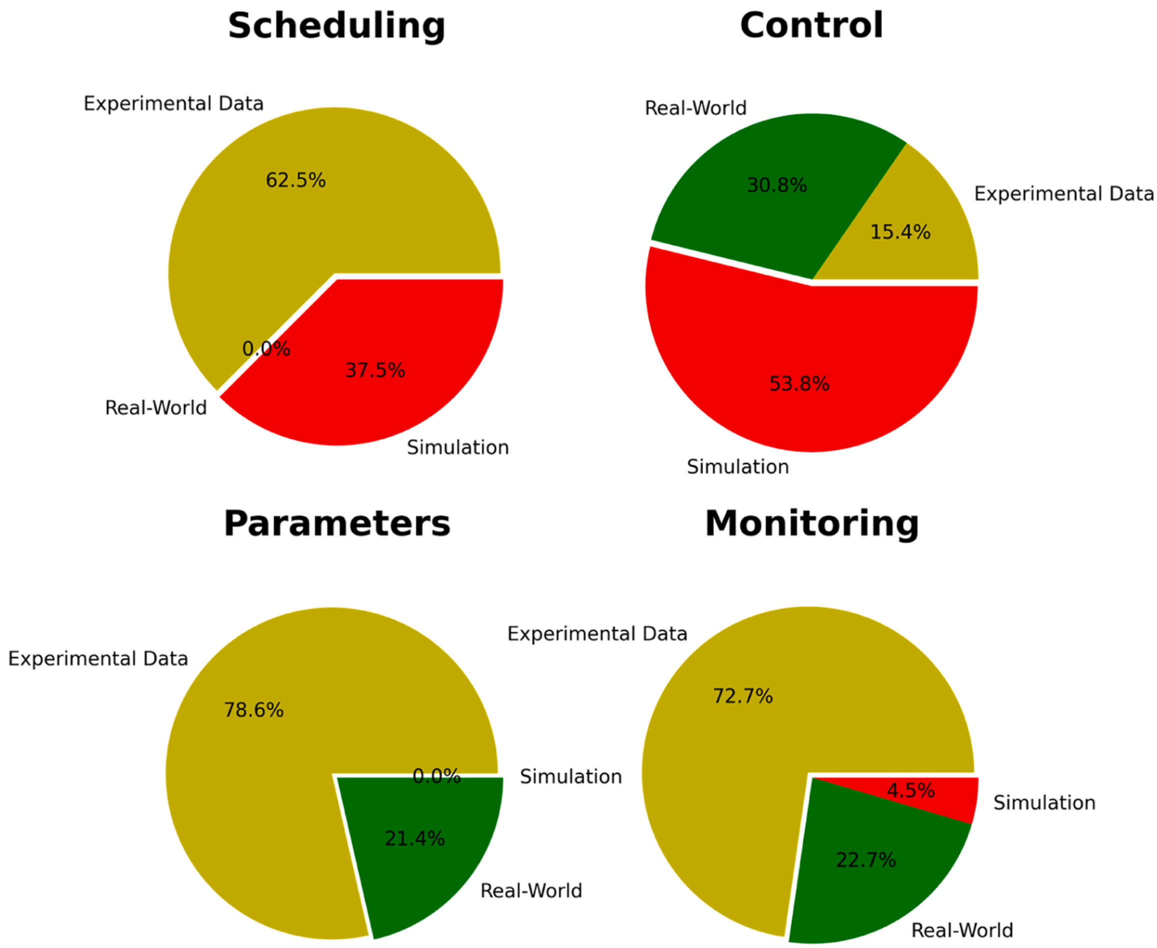

Fig. 8. Demonstration of the extent of validation of the proposed AI-driven solutions for the challenges of energy-efficient manufacturing systems.

Table 2
Frequently used keywords in publications from 2013 to 2024.

Keywords	Count	Keywords	Count	Keywords	Count
Energy consumption	47	Sustainable manufacturing	10	Production systems	6
Energy efficiency	42	Deep learning	9	Energy management	6
Machining	25	Decision making	8	Forecasting	6
Reinforcement Learning	13	Multi Objective Optimization	7	Machine tools	6
Manufacturing process	12	Optimization	7	Energy conservation	6
Neural Network	11	Industrial research	7	Cutting tools	5
Learning algorithms	11	Machine Learning	7	Life cycle	5
Learning systems	10	Sustainable development	6	Markov processes	5

efficiency challenges AI addresses, the AI-driven methodologies employed to solve these challenges, or the outcomes and limitations of AI-driven solutions in practice. Consequently, a qualitative analysis is required to investigate these aspects further, offering deeper insights into the practical implications and future potential of AI in enhancing energy efficiency in manufacturing systems.

4. AI-driven solutions for energy-efficient manufacturing system

While the bibliometric analysis in the previous section demonstrates the trends and focuses of studies on AI-driven solutions for manufacturing systems, this section aims to provide a qualitative literature review to investigate the identified challenges and propose solutions as presented in the existing papers.

Table 3 provides an overview categorizing the papers based on three issues that this paper focuses on and discussed earlier: First, four primary energy challenges, including (1) Monitoring and Prediction, (2) Real-Time Control, (3) Scheduling, and (4) Parameters Optimization; second, the utilization of AI, distinguishing between AI as the main solution (based) and AI as a support for the main solution (aided); and third, the general forms of the prosed solutions, involving ML, NN, DL, and RL. Moreover, in Table 4 a comparison between the AI approaches based on the proposed solutions by the reviewed papers is proposed.

In the following section, the proposed data-driven solutions from the literature to address the identified energy efficiency challenges are investigated, and the details related to the utilized algorithms are presented in the tables. The columns in the tables include:

- Objective: This refers to the targeted objective(s) for energy efficiency, such as energy consumption, energy cost, etc.
- Input and Output: These columns specify the input data utilized by the algorithms and the output data generated by them. For RL-based or aided algorithms, the input is considered as states' information, and the output is actions. The typical input and output data for AI algorithms can be divided into two categories: manufacturing and non-manufacturing data. Manufacturing data can originate directly from the manufacturing system at various levels (e.g., component-level, machine-level, or line-level data) or from other sources related to the manufacturing system. Component-level data pertains to the machinery's components or machine tools, while machine-

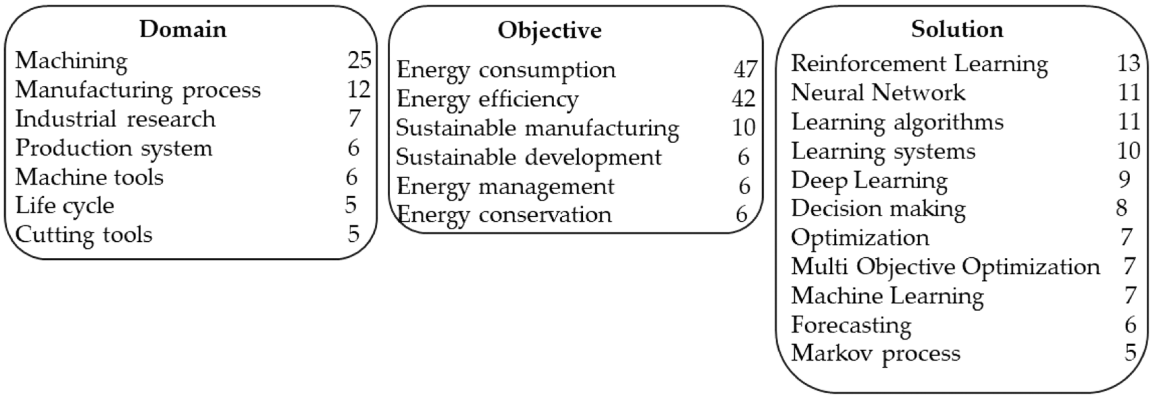

Fig. 9. Categorized the used keywords.

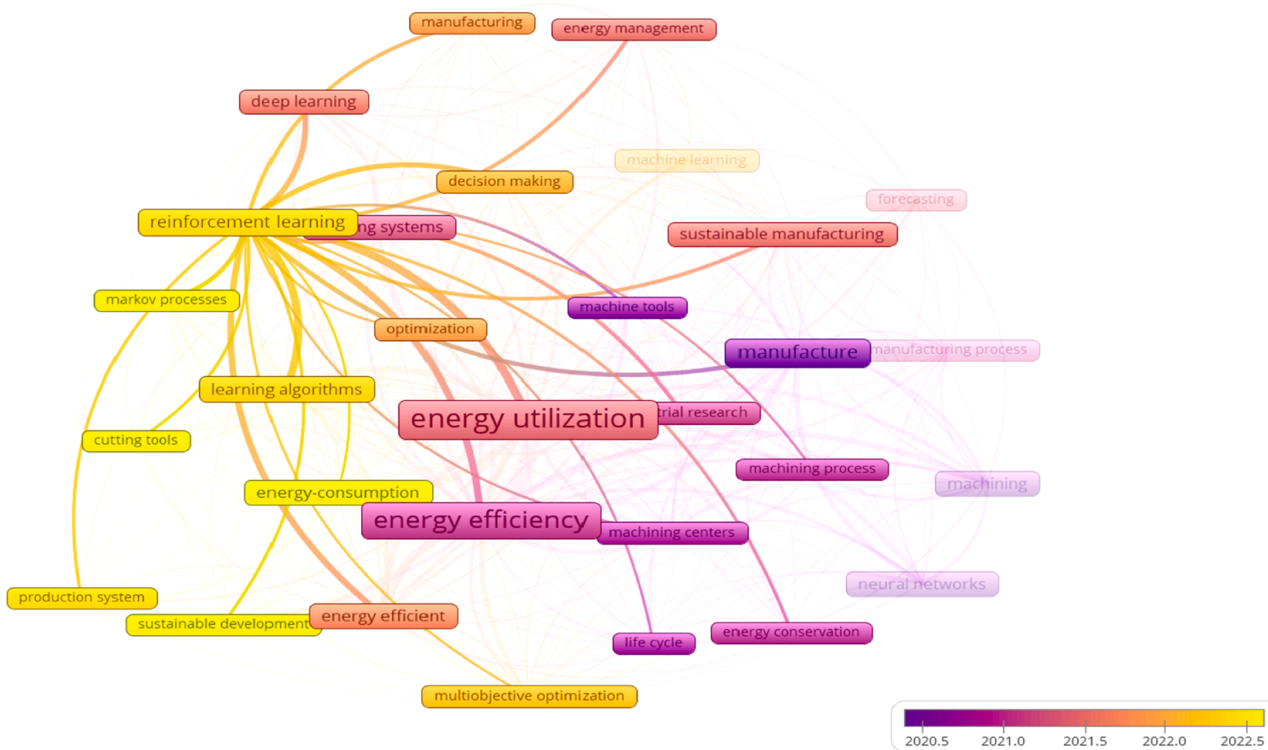

Fig. 10. Overlay visualization of keywords co-occurrence network, emphasizing AI related keywords.

level data includes parameters such as cutting speed, and line-level data involves the status of production equipment and process parameters (e.g., temperature). Other sources of data include job-related information (e.g., sequence of operations), electricity grid data (e.g., electricity price), weather data (e.g., temperature), and time-related features (e.g., calendar effects). Non-manufacturing data refers to inputs and outputs where AI is not the primary solution but is applied to improve an existing method.

- Testbed: This indicates the extent to which the validation bed of the proposed methodology resembles the real world. "Simulation" means it is tested in a virtual environment or using generated data, "Experimental data" means it is validated using real-world data but not in online mode, and "Real-world" means the solution is validated in a real environment.
- Controlling Variables: This refers to the controllable variables toward energy efficiency in the problem. Controlling variables is particularly meaningful for problems that involve not just data analysis but also decision making, such as Scheduling, Real-Time Control, and Parameters Optimization. Similar to input and output data, controlling variables can be classified into manufacturing and non-manufacturing variables. Manufacturing variables correspond to various system levels (e.g., component-level, machine-level, or line-level variables). Component-level variables are related to specific machinery parts, while machine-level variables pertain to machining processes like cutting speed. Line-level variables involve the status of production line equipment and process parameters. Job-related variables, such as operation sequences, are also considered. Non-manufacturing variables refer to algorithmic factors applied when AI is not the main solution but serves to enhance the primary solution.

Table 3
General information.

Challenge	AI- based or aided	AI branch	Literatures
Monitoring and Prediction	Based	ML	19, 30, 31, 32, 34, 39
		NN	24, 25, 26, 27, 28, 29, 36
		DL	18, 19, 20, 21, 22, 23, 35, 37, 38
Real-Time Control	Based	RL	40, 41, 42, 49, 50,51
	Aided	ML	44, 45, 46, 47, 48
		NN	43
		DL	52
Scheduling	Based	ML	54
		NN	63
		DL	55
		RL	53, 61, 62, 66, 67
	Aided	ML	60
		NN	59
		DL	60, 65
		RL	56, 57, 58, 64, 68
Parameters Optimization	Based	NN	80
		RL	69, 70
	Aided	ML	77
		NN	71, 72, 73, 74, 75, 76, 78, 79, 82
		DL	81

4.1. Monitoring and prediction

Monitoring and Prediction for energy efficiency have been addressed in various studies at the machine, and production line levels. This is considered foundational for energy-efficient Scheduling, Real-Time Control, and Parameters Optimization. Research in this area encompasses a range of subproblems, including energy consumption prediction, pattern recognition, remaining useful life prediction, human-machine interaction, and fault diagnosis. These subproblems can be divided into two main categories: 'Energy Analytics,' which covers energy consumption prediction and pattern recognition, and 'Predictive Monitoring,' which includes remaining useful life prediction, fault diagnosis, and human-machine interaction.

The proposed solutions in these subclasses primarily focus on data analysis rather than decision-making and are based on AI, specifically shallow and deep NNs and classical ML approaches. To better present these solutions, in the following, each subproblem is investigated from the perspective of the AI algorithms used, involving shallow NNs, DL and classical ML algorithms. Overall, DL algorithms, specifically LSTMs, are the most commonly applied algorithms for both subproblems, Energy Analytics and Predictive Monitoring. Moreover, typical inputs and outputs involve manufacturing data at various levels, as well as other sources data like electricity grid data and time-related features.

4.1.1. Energy analytics

The objective of the Energy analytics is to develop a model for predicting energy consumption and recognizing energy patterns. For these purposes, several papers suggest using deep NNs architectures, such as LSTMs and CNNs. In [25], an LSTM optimized by an improved PSO algorithm is used to predict energy consumption for a milling machine. Similarly, in [26], a human-machine interaction framework employs an LSTM to predict energy consumption in a system including a 3D printer, a personal computer, and a production line. This framework integrates the YOLO algorithm, Character-Region Awareness For Text Detection-based models, and RGB image-based Skeleton estimation to interpret human-machine interactions. Furthermore, the integration of convolutional-based networks with GRUs, a lighter version of LSTM, is suggested by [27] and [28] to incorporate spatial along with temporal features for prediction tasks. In [27], a GCN and in [28], a CNN are used to understand the relationships among nodes representing production processes in aluminum profile factories to assist the GRU in predicting energy consumption across multiple nodes simultaneously. LSTM is also employed in a pattern clustering framework, as proposed by [29]. This framework involves a two-stage clustering process utilizing the integration of FCM, LSTM, and four key performance indicators for clustering energy consumption patterns in a Slag Grinding Production System. The effectiveness of three deep NN architectures and three ML algorithms is assessed in [30], comparing energy consumption prediction accuracy and training time across two scenarios. In the first scenario, which involves predictions without considering the deterioration of spindle motors and cutting tools, ANNs, SVR, and GPR are evaluated. In the second scenario, which accounts for spindle motor aging and tool wear, a CNN, a Stacked Autoencoder, a Deep Belief Network, and the ML algorithms are compared.

The utilization of shallow NNs architectures is suggested by several papers for tasks like energy consumption modeling and energy pattern recognition. In [31], an optimized Back Propagation NN, which its architecture is not clarified using PSO is proposed as the energy prediction mechanism within a four-layer service-oriented energy assessment system. [32] suggests a two-layer ANN for identifying the most influential factors on energy consumption and predicting energy consumption in CNC machining processes. In [33], various architectures of simple Feed Forward NNs, including different numbers of layers and neurons, are compared for estimating energy consumption during operations in remote laser welding, particularly in the assembly process of car rear doors under two different modes. Mode one utilizes basic operational features, while mode two incorporates more complex variables to capture subtler influences on energy use. [34] introduces a boosted one-layer NN as a predictive model within a step-by-step conceptual framework for addressing real-world energy problems. This algorithm is chosen over compared methods, including SVR and RF, in a steel manufacturing plant. Additionally, K-means clustering is utilized for the electricity consumption scenario generation section of this framework. Both [35] and [36] suggest the use of multi-layer ANN for energy pattern recognition. Specifically, [35] recommends a three-layer ANN for a production line, while [36] advocates for a two-layer ANN for two injection molding machines.

Some authors suggest the utilization of classical ML algorithms, such as RF, Decision Tree, etc., for energy consumption modeling. In [37], the authors introduce RF as a more accurate algorithm compared to Decision Tree and Boosted RF for predicting energy consumption in various CNC machining operations. In [38], the utilization of GPR, a nonparametric ML technique, is suggested for modeling energy consumption of machine tools. Polynomial Regression and Linear Regression are proposed in [39] as prediction algorithms within a seven-step framework developed to create a data-driven DT for technical building services. These algorithms are chosen over others, including simple Regression Tree, Gradient Boosting Trees Regression, Multi-layer Perceptron Regression, and Naive Bayes, based on performance comparison on data from cooling towers. In [40], the authors propose integrating Gaussian Kernel Extreme Learning Machine, Petri-net models, and DT prototypes to develop an energy consumption model for aluminum extrusion and die-casting workshops. In [41], the FCM algorithm is employed as part of a process to calculate surface machining complexity. This algorithm is used to partition the sculptured surface into regions with similar curvature characteristics, thereby assisting in evaluating the complexity of the surface and its impact on energy consumption and efficiency in CNC machining. For further details regarding the methodologies discussed, refer to Table 4.

4.1.2. Predictive monitoring

The objective of predictive monitoring is to develop a model that can predict the remaining useful life of devices, detect faults, defects, and anomalies, and understand human-machine interactions. For these purposes, NNs, particularly DL approaches, are widely employed. LSTM, as described by [42], and a two-layer ANN, recommended by [43], are utilized for predicting the useful life of mobile industry robots' batteries and a CNC machine in steel processing under dry cutting conditions,

Table 4
AI approaches comparison.

Aspect	ML	NN	DL	RL
Core Concept	learning from data to make prediction or decisions and classifying data points.	A subset of ML that uses interconnected layers of nodes (neurons) to model moderate complex relationships in data for making prediction, decisions or classifying data points.	A specialized type of NN with multiple layers (deep architectures) for modeling high complex relationships in data for making prediction, decisions or classifying data points.	A learning paradigm where an agent interacts with an environment to maximize cumulative rewards through trial and error.
Typical usage in manufacturing context	Main solution in Monitoring and Prediction. Support for the main solution in the Real- Time Control.	Main solution in Monitoring and Prediction. Support for the main solution in the Parameters Optimization.	Main solution in Monitoring and Prediction. Support for the main solution in the Scheduling.	Main solution in Scheduling and Real-Time Control.
Interpretability	Highly interpretable, offering transparency in decision-making, making it easier to understand by non-technical staff.	Less interpretable due to hidden layers, making it harder to explain to end-users.	Considered a "black box" due to deep architectures, which makes it challenging to explain the model's decisions to stakeholders.	Interpretation is difficult due to learned policies and the complexity of interactions between the agent and environment.
Data Requirements	Performs well with small to medium-sized datasets, which can be a practical advantage when data collection is costly or time-consuming in manufacturing.	Requires more data, especially as the network complexity increases. This may be a limitation in environments with limited data availability.	Requires large datasets, which can be impractical in manufacturing environments where high-quality data is scarce or expensive to collect.	Can work with various data sizes, but often requires extensive resources for interaction with the environment, which may be infeasible in real-world manufacturing setups.
Feature Engineering	Requires manual feature engineering, demanding domain expertise and effort, which could be a challenge for companies without skilled teams.	Some feature learning capabilities, but often relies on pre-engineered features, which still requires significant domain knowledge.	Automatically learns feature representations from raw data, reducing the need for domain knowledge.	Learns features through interaction with the environment.
Training Time	Typically, fast, especially for simpler models. Shorter training times can be an advantage in real-time manufacturing applications where quick deployment is needed.	Training time increases with network complexity, which may be a limitation in time-sensitive manufacturing environments.	Often requires substantial training time due to large datasets and deep architectures, posing a challenge for real-time or resource-constrained manufacturing systems.	Time-consuming due to exploration and interaction with the environment, often requiring many iterations, which could make real-time implementation infeasible in certain manufacturing contexts.
Computational and Implementation Cost/ Resources Requirements	Low computational and implementation cost. Can often run on standard CPUs, which makes it cost-effective in manufacturing environments with limited budgets.	Moderate computational cost, with benefits from GPUs. This may increase costs for companies without advanced hardware setups.	High computational and implementation costs, typically requiring GPUs or TPUs. The cost of such hardware can be a barrier for small or medium-sized manufacturing companies.	Extremely high computational costs, often requiring distributed computing resources for simulation and training, making it impractical for many manufacturing applications.
Exploration/ Exploitation	Focuses on learning from provided data, with limited adaptability to changing environments without retraining.	Focuses on learning from provided data. Moderate adaptability to changes but still requires retraining.	Focuses on learning from provided data. Highly adaptable through transfer learning but requires substantial computational power for fine-tuning.	Balances exploration and exploitation, making it suitable for dynamic environments, but the trial-and-error nature may be resource-intensive and difficult to implement in highly structured manufacturing setups.
Adaptability	Less adaptable to changes. Often requires retraining with new data.	More adaptable than traditional ML, but still requires fine-tuning for new tasks.	Highly adaptable through transfer learning and fine-tuning, making it suitable for rapidly evolving tasks.	Highly adaptable to dynamic environments, continuously learns and adjusts policies.
Ability to Handle Noise and Incomplete Data	Moderate ability to handle noise, but performance can degrade with high levels of missing data, posing a risk in manufacturing environments with unreliable data collection.	Moderate to high ability to handle noise, but significant levels of missing data can still impact performance.	Robust to noise, but high levels of missing data can still degrade performance, which may limit its application in noisy or incomplete manufacturing datasets.	High ability to handle noise and incomplete data by learning to adapt through interaction with the environment, though this is resource-intensive and may not always be practical.

respectively. In [44], an optimized Fuzzy Attention-based Bidirectional LSTM, enhanced by the Moth Flame Optimization algorithm, is used in a fault diagnosis framework for rotating machines. This framework also leverages Empirical Mode Decomposition to decompose faulty signals and PCA to reduce the features of the faulty data. A defect detection framework is proposed in [45], which incorporates the Residual Network and YOLO architectures for feature extraction, defect localization, and classification of metal gear end-faces.

Classical unsupervised ML methods, such as K-means, are utilized to develop an anomaly detection frame in [46], which aims to identify anomalies and inefficiencies in energy consumption. This paper underscores the importance of proposing human- understandable and interpretable methods, enabling factory managers and operators to comprehend and trust the decisions and insights produced by the system. To gain further insights into the methodologies, refer to review Table 5.

4.2. Real-Time Control

Energy-efficient real-time control in the manufacturing scope can be defined as controlling the components of a production line (line level) or several production lines (manufacturing level) within specific time constraints to achieve energy efficiency objectives. Controlling the components, such as machines, can enhance energy efficiency in several ways, such as by the management of idle times.

The two main objectives considered by the reviewed papers in this energy efficiency challenge are energy consumption and energy cost. Accordingly, this review investigates the control strategies designed by these papers in two subclasses: Real-time energy consumption-based control and real-time energy price-based control. It is worth

Table 5
Energy analytics.

Literature	Objective	Input	Output	Testbed
[18]	Energy consumption	Current, voltage, power, spindle speed, feed speed, depth of cut, number of blades, energy consumption.	Predicted energy consumption.	Experimental Data
[19]	Human-machine interactions status, and devices' energy profiles prediction	LSTM algorithm: Aggregated power consumption of the devices. Human-machine interaction framework: Different cameras' images.	LSTM algorithm: Disaggregated power consumption of the devices. Human-machine interaction framework: Detected objects, identified fingers' positions, recognized texts and detected workers' motions.	Real-world
[20]	Energy consumption	GCN: Adjacency matrix and periodical energy consumption. GRU: The output of the GCN.	GNN: The spatial relationship between nodes. GRU: The predicted energy consumption.	Experimental Data
[21]	Energy consumption	CNN: Energy consumption patterns. GRU: Extracted features by CNN and auxiliary nodes data.	CNN: Spatial distribution and relationships between energy nodes. GRU: Energy consumption.	Experimental Data
[22]	Pattern recognition	First clustering stage: Energy consumption. Second clustering stage: Auxiliary information and labelled energy consumption of the previous stage. Prediction stage: The clustered data of the second clustering stage.	First clustering stage: Energy consumption. second clustering stage: Clustered energy consumption and auxiliary information. prediction stage: The predicted future energy consumption.	Real-world
[23]	Energy efficiency	Simulated data includes tool type, cutting strategy, trajectory, and machining parameters. Monitoring data encompasses machine state, instantaneous power, tool wear, and motor temperature. Derived data, stored in the existing production management system comprises detailed information about operations, machines, tools, workpieces, and cooling mechanisms.	Prediction of energy efficiency.	Simulation and Experimental Data
[24]	Energy consumption	Machining features, process activities, and process parameters, including spindle speed, feed, and depth.	Energy consumption of working state, including start-up, standby, acceleration/ deceleration, air cutting, and cutting.	Experimental Data
[25]	Energy consumption	Spindle speed, feed rate, and cut depth.	Energy consumption	Experimental Data
[26]	Energy consumption	Mode one: Basic operational features, such as initial laser power and process time. Mode two: Basic operational features and derived advanced features, such as cooling time, duration of welding phases, etc.	Energy consumption.	Experimental Data
[27]	Energy consumption	K-means and Boosted NN: Scrap types, direct reduced iron, melting additives, equipment age, energy consumption (for k-means).	Boosted NN: Predicted energy consumption. K-means: Grouped production scenarios.	Real-world
[28]	Energy consumption and Productivity	Voltage and Current.	Categorized Energy patterns.	Experimental Data
[29]	Energy consumption	Time series energy vectors.	Energy consumption patterns.	Real-world

(continued on next page)

Table 5 (*continued*)

Literature	Objective	Input	Output	Testbed
[30]	Energy consumption	Numerical control instructions, such as spindle speed. Derived hidden information form numerical control instructions, such as the diameters of the tools.	Energy demand for different CNC machine tool aggregates, including the x, y, and z axis, spindle, and tool change system.	Experimental Data
[31]	Energy consumption	Feed rate, spindle speed, depth of cut, cutting direction, cutting strategy.	Energy density.	Experimental Data
[32]	Electricity power demand and Cooling capacity	Temperature of ambient air, water tanks and cooling towers, number of active cooling towers, activity of the heat sources and connected pumps, pressure level, volume of water flow, electrical conductivity, pumps and fan speed, ambient air humidity, time (hour and day of the week).	Polynomial Regression: Cooling capacity Linear Regression: Electric power demand.	Experimental Data
[33]	Energy consumption	Operating and working condition parameters.	Instantaneous firing speed of energy consumption continuous transition in each operation states.	Experimental Data
[34]	Energy consumption and efficiency	Surface Rough Partitioned.	Surface Fine Partitioned.	Experimental Data

mentioning that, in some cases, other objectives, such as production time reduction, are also considered alongside the main objectives, but the reviewed papers are organized based on two commonly focused and highly related objectives to energy efficiency.

In the subsequent sections, the proposed solutions for each subproblem are discussed from the perspective of AI-based and AI-aided solutions. Generally, the DRL approaches, particularly DQN and AC, are widely used algorithms for energy-efficient real-time control (across both subclasses) and are typically applied as the primary decision-makers. Moreover, Typical input and output data include line-level data, electricity grid data, and weather data, with controlling variables primarily at the line level.

4.2.1. *Real-time energy consumption-based control*

In this subproblem, the objective is to control the components of production line (or lines) in real-time based on energy usage. To this end, AI-based control solutions are proposed in several papers. Paper [47] recommends the Advantage AC, utilizing Radial Basis Function NNs as function approximators, for controlling individual manufacturing devices within a hybrid system that exhibits both discrete and continuous behaviors. Paper [48] employs the DQN to find the optimal control policy for a single workstation producing cylinder heads, which includes identical parallel machines. Meanwhile, paper [49] uses the PPO agent for multi-stage production lines involving parallel machines. Surprisingly, in the case of the single workstation, the DQN outperforms the PPO, whereas for multi-stage production lines, the PPO shows better performance compared to the DQN.

The use of AI as a support mechanism for the primary control solution is suggested by several other papers. In [50], the designed decision making process utilizes the prediction of machines idle periods from the integration of a Gaussian Mixture Model with a four-layer NN to select optimal energy control actions. The proposed method in this paper is validated using an automated assembly simulator system. In [51], the Honey Badger Algorithm-Histogram-based Gradient Boosting Regression Tree predictions are proposed to enhance the search for optimal control solutions within the framework of NSGA-II. In [52] the author proposes the utilization of the SVR for predicting indoor temperature to inform a GA that determines the optimal settings for both the Make-Up Air Unit and Dry Cooling Coils in air conditioning systems on the shop floor. In [53], a two-phase energy-efficient state control strategy for manufacturing equipment is proposed. In phase one, the integration of MLE and KDE is utilized to estimate machine idle time. In phase two, the estimations are utilized in the optimization process. Similarly, in [54], the use of KDE for modeling the stochastic nature of machine idle times is suggested. Additionally, the RuLSIF algorithm is applied for adaptive detection of significant changes in the manufacturing process that could affect machine idle times. The information derived from the KDE and RuLSIF are utilized in an optimization procedure. In [55], the KNN algorithm is employed within an intelligent rework process management system in a steel manufacturing context to enhance decision-making. This system strategically targets items with potential defects, redirecting them for rework prior to undergoing quality testing. Among various conventional classification algorithms evaluated, including Decision Trees, Naive Bayesian classifiers, and RFs, KNN was chosen for its superior performance in accurately classifying potentially defective items. For additional information on the methodologies discussed, refer to Table 6.

4.2.2. *Real-time energy price-based control*

In Real- time energy price-based control, the objective is to control the components of the production line (or lines) in real-time, based on electricity price signal, with the goal of reducing energy cost. In [56], a Multi-Agent AC framework using PPO is employed to control production machines in a flexible manufacturing system under uncertainties, such as future weather-based energy prices. Each agent, responsible for a specific manufacturing component, is trained in various competitive and cooperative scenarios to explore different energy efficiency strategies. Utilization of DQN-based algorithms to determine optimal control policies are proposed by [57] and [58]. In [57], a Decomposed Multi-Agent DQN is applied to control a section of an assembly line. The implementation of Decomposed Multi-Agent DQN not only makes actions interpretable by decomposing tasks among the agents but also outperforms traditional DQN. This paper demonstrates that performing real-time control yields better results compared to day-ahead scheduling. In [58], Double DQN are utilized for performing intelligent switching in a manufacturing system, powered by energy storages and public electricity grid. Switching based on two DQN addresses the issue of overoptimistic value estimation.

The only work proposing AI as a support for main decision maker in this subproblem is [59]. In this paper, the authors propose leveraging LSTM predictions to guide Gurobi Solver in controlling steel powder

Table 6
Predictive Monitoring.

Literature	Objective	Input	Output	Testbed
[35]	Maintenance	Operational usage data, including pressure measurements, temperature measurements, vibration measurements, voltage, current, datetime stamps, capacity values. Other available databases at the workshop level.	Remaining useful life.	Real-world
[36]	Maintenance	The cutting speed, feed, depth of cut, and white pixel counts.	Wear amount and remaining tool life.	Experimental Data
[37]	Fault diagnosis	Vibration signals from the rotating machinery.	Classified faults, including bearing faults, misalignment of shaft axis, gear defects, and other mechanical faults.	Experimental Data
[38]	Defect detection	Images of common defects of the metal gear end face, including scratches, bumps, and dents, within a gear manufacturing workshop.	localization and classification of the defects.	Experimental Data
[39]	Energy consumption	K-means and PCA: Energy consumption data.	K-means: Clustered energy consumption patterns. PCA: Reduced size of energy consumption data's feature space.	Experimental Data

manufacturing process. Further details on the methodologies discussed are outlined in Table 7.

4.3. Scheduling

The scheduling challenge is a significant topic within the field of energy-aware manufacturing systems. It is commonly addressed in studies at both the line level and the manufacturing level. The objective of this challenge is to improve energy efficiency through optimal task allocation and resource planning. Accordingly, the current review classifies scheduling-related papers into three subclasses: Task allocation, which focuses on allocating tasks optimally; resource allocation, which concentrates on planning resources optimally; and task allocation and resource planning, which addresses both problems simultaneously.

In the following sections, proposed solutions for each subproblem are discussed from the perspective of AI-based and AI-aided solutions. Generally, to address the mentioned challenges, RL approaches, particularly the DQN and QL algorithms, are extensively employed. Moreover, typical input and output data include component, machine, line-level, and job-related data, with controlling variables at the machine and line levels.

4.3.1. Task allocation

In the task allocation problem, the primary focus lies in the nature of the jobs themselves, such as sequencing operations within a job optimally to achieve the objectives, such as minimize energy consumption or reduce energy costs. It's important to note that while focusing on task allocation does touch upon resource management, the primary emphasis of papers in this category is on optimizing job characteristic rather than resource allocation.

For optimal task allocation, RL is applied as the main decision-maker in [60], while ML is employed in [61] and [62]. To be more specific, in [60], for discovering the optimal sequence of order acceptance, the authors propose integrating CNN's predictions to guide both model-free and model-based RL in two scenarios: Massive and one-by-one order arrivals. The targeted manufacturing process is Printed Circuit Board production, known for its energy-intensive and pollution-intensive nature. In [61], the authors propose a two-step decision-making procedure based on an Ensemble Deep Forest to select the optimal scheduling strategy in flexible job shops. The first step involves the One-Versus-All strategy, which simplifies complex multi-class classification into manageable binary problems. In the second step, a cascaded forest structure is utilized, incorporating XGBoost, Extra Trees, RF, and Logistic Regression, to further refine the decision-making process. In [62], three Fully Connected Deep (five-layer) NNs, trained on optimized scheduling plans, are suggested to predict optimal schedules for a flow shop. Additionally, the Arena 2018 simulation and modeling package is employed to evaluate the generated schedules.

Regarding AI- related methodologies, in [63] and [64], QL is proposed to enhance the performance of optimization techniques. Specifically, in [63], QL is employed to improve the local search of Multi-Objective PSO, which is utilized for distributed flow-shop scheduling. In [64], Multi-Objective QL is deployed to enhance the selection process of the Hyper Heuristic Algorithm with bi-criteria selection for mixed-shop scheduling. With a similar idea to [64], but utilizing different learning approach, [65] presents an RL-based policy agent and a policy network, including an embedding layer, a multi-head attention network, and several linear layers to augment the selection capability of the Cooperative Memetic Algorithm for hybrid flow-shop scheduling.

Some other papers propose non-RL related solutions to address this challenge. In [66], two Multi-layer ANN are utilized as monitoring models for abnormality detection and energy model for energy prediction, guiding Fruit Fly Optimization technique for scheduling and rescheduling under dynamic and aging conditions of CNC machines. With a similar idea to [66], but utilizing different learning and optimization approaches, [67] introduces an architecture utilizing FCM, LSTM, and NSGA-II for data partitioning, anomaly detection, and rescheduling decision-making based on the type of the detected anomaly in a milling manufacturing system at an elevator workshop. Additional information on the methodologies discussed is provided in Table 8.

4.3.2. Resource planning

In the context of energy-efficient resource planning, the central objective is to strategically plan available resources, such as operational states of machines within a manufacturing system to optimize energy utilization, energy cost, etc. It's noteworthy that while resource planning inherently involves considerations of task allocation, the predominant focus of research in this domain is directed towards optimal resources utilization rather than job allocation.

For optimal resource planning, [68] and [69] apply RL and [70] applies a shallow NN architecture as the main decision-making tools. In [68], a Multi-Agent Deep Deterministic Policy Gradient framework, which includes decentralized actors' networks and a centralized critic's

Table 7
Real- time energy consumption-based control.

Literature	Objective	Input	Output	Controlling variables	Testbed
[40]	Energy consumption	State- space: The status of the buffer stations and mini hoppers. Actor network: States. Critic network: State-action pairs.	Actions: Setting vacuum pumps priming time, and belt conveyer speed and turning conveyer on/off. Actor network: Means and standard deviations of a gaussian distribution, which are then used to sample the actions. Critic network: Predicted value function.	Same as the agent's action.	Experimental Data
[41]	Energy consumption and productivity	Working States of Each Machine and Number of Parts in Buffer.	Turning machines in each station on/off.	Same as the agent's action.	Real-world
[42]	Energy consumption and productivity	Number of machines in working state and parts in buffers.	Turning machines on/off.	Same as the agent's action.	Real-world
[43]	Energy consumption	Production throughput, energy consumption, buffer state, machine state, and failure rate.	Idle Duration of the machines.	Switching machine between the ready for operation and hibernation mode.	Simulation
[44]	Energy efficiency, throughput, and energy consumption	Total buffer capacity and total service rate.	The throughput, energy consumption, and energy efficiency.	Buffers' capacity and the service rate of the machines.	Simulation
[45]	Energy consumption and temperature	Indoor condition, including current shop floor temperature, operation condition, such as cooling capacity and historical energy use such as dry cooling coil energy consumption.	Temperature of the shop floor.	Make-Up Air Unit set point and Dry Cooling Coils openings.	Experimental Data
[46]	Energy consumption	MLE and KDE: Part arrival time.	MLE: Estimated parameters, that quantitatively define the stochastic process of part arrivals. KDE: Estimated density function and probability density of part arrivals.	Turning machines on/off.	Simulation
[47]	Energy consumption	KDE: Parts arrival time. RuLSIF: Parts arrival time and pre and post change point data.	KDE: Estimation of probability density function of machine idle times or part arrivals. RuLSIF: Change point score and identified change points.	Switching among idle, standby and startup states.	Simulation
[48]	Energy consumption	Single element content, like manganese, represents the composition of materials, combination of multiple element contents and working condition parameters, such as cooling time.	Quality Label (good or bad).	Redirection of items predicted to be of bad quality.	Real-world

Table 8
Real- time energy price-based control.

Literature	Objective	Input	Output	Controlling variables	Testbed
[49]	Energy cost	State- space: Operational state of the components, target load of the grid, current time step within the production shift, the amount of the production tasks to be executed and current energy price. Actor network: States. Critic network: State-action pairs.	Actions: Controlling states of the operational machines. Actor network: Probability of choosing each possible action. Critic network: Predicted value function.	Same as the agent's action.	Simulation
[50]	Energy cost	Buffer states, current time, current electricity price and sharable information among the agents.	Turning on/off workstations.	Same as the agents' actions.	Simulation
[51]	Energy cost	The state of charge of the energy storage equipment, predicted power requirements of the manufacturing system, and the electricity price ratio.	Switching to energy storage equipment and reverting to the public electricity grid.	Same as the agent's action.	Simulation
[52]	Energy cost	Dynamic energy demand, electricity price, varying current, lagged weather temperatures and static calendar effects.	Predicted price.	Shifting shiftable and controllable loads.	Real-world

network, is used to optimally schedule machines in discrete manufacturing systems based on the demand response. In [69], a Double DQN explores optimal scheduling policies for AGVs with battery replacement, leveraging the benefits of using two DL algorithms to enhance stability. In [70], each machine is equipped with an two-layer NN and a Transfer Learning strategy for predicting machining energy in both the presence and absence of data. Additionally, various agents, such as a product agent, are employed to perform tasks, such as assigning tasks to machines with lower predicted energy consumption for those tasks.

In other studies, AI is utilized to enhance primary solutions. In [71], a Double DQN, is deployed to improve the selection process of the Hyper Heuristic Algorithm for conflict-free scheduling of AGVs in a flexible manufacturing system, consisting of multiple manufacturing cells. In

[72], an Encoder-Decoder LSTM network and a newly defined loss function guide a PSO algorithm for production scheduling based on demand response. The DL architecture utilized in this paper is optimized by a GA. Details regarding the methodologies discussed are outlined in Table 9.

4.3.3. Task allocation and resource planning

Some authors attempt to address both the challenges of task allocation and resource planning simultaneously. While the utilization of RL-based solutions for addressing these challenges together is suggested by [73] and [74], [75] proposes the utilization of RL to improve an optimization technique. To be more specific, in [73], the application of GCN to assist RL agents in process planning is proposed. In this paper, first, the decision variables are transformed into a graph structure with MDP properties. Then, a GCN is utilized to compress the input graph's topology, and finally, RL agents are applied to generate the process plans. Additionally, to enhance the adaptation performance of the RL assisted by GCN, a two-phase multitask training strategy is applied. In [74], the author addresses simultaneous flexible process planning and machining parameters optimization by employing an AC framework with the PPO algorithm. The proposed solution was benchmarked against four meta-heuristics, such as NSGA-II, under two scenarios: A static manufacturing environment and variations in machining resources. In [75], QL is suggested to improve the exploration of the Cooperative Co-evolutionary Algorithm via sub-swarm size adjustment. The problem is flexible job shop cell scheduling, which is formulated as Mixed-Integer

Table 9
Task allocation.

Literature	Objective	Input	Output	Controlling variables	Testbed
[53]	Production cost, makespan, and carbon emission, caused by energy and chemical	CNN: PCB order related features, including, board layout, circuit features, delivery and logistics, substrate material, manufacturing features, manufacturing system status, and resources consumption. The state space: Order arrival time, instant production capacity, order attributes, such as delivery date and cleaner production indicators, such as carbon consumption.	CNN: Production cost, makespan, and carbon consumption. Actions: Accepting or rejecting the orders.	Same as the agent's action.	Experimental Data
[54]	Carbon emission, caused by energy consumption.	One-Versus-All: Fourteen features related to performance degradation, adaptation capability, and process phase. Ensemble Deep Forest: The output of the One-Versus-All.	One-Versus-All: A binary vector representing the chosen scheduling strategy. Ensemble Deep Forest: One of the four predefined decisions.	Choosing a scheduling strategy among, right shift rescheduling, partial rescheduling, total rescheduling, and inverse scheduling.	Simulation
[55]	Energy cost and makespan	Batch sizes, sequences in which these batches are to be processed and scheduling information for different machines.	Operational planning, including parallel Machines numbers and every single product's starting processing time.	Same as the output.	Experimental Data
[56]	Energy consumption and makespan	"Better solution" and "Inferior Solution" indicate whether the solution is superior or inferior, respectively, to the one obtained from the local search strategy.	Selecting a factory set among the available ones.	Assigning jobs to the factories and machines.	Experimental Data
[57]	Makespan, and total energy consumption	Cumulative running time and termination time.	Choosing an optimizer from the Grey Wolf operator, Jaya operator and Crossover operator.	Sequence of the products and the speed level of the operations.	Experimental Data
[58]	Makespan and the energy consumption	Instance information, current solution, and history of actions and effects.	Choosing the search operator among the introduced ones in three classes of inner adjustment, inter adjustment and weight adjustment.	Adjusting the job sequence in the factory and among factories and determining job processing priorities.	Simulation
[59]	Energy consumption and productivity	The energy model: Components related features, including precision requirement, machining feature quantity, material, and machining volume. The monitoring model: Components representing CNCs' energy consumption patterns.	The energy model: Predicted energy consumption and machining time. The monitoring model: Components' operation type.	Assignment of components to CNC machines	Experimental Data
[60]	Energy consumption	Energy feature parameters, including statistical ones such as the standard deviation of energy consumption, and data derived from preprocessed energy consumption across different states, such as standby during the machining process.	Three types of production anomaly statuses, involving no anomaly, machine tool degradation and tool wear.	Choosing a scheduling strategy among, no rescheduling, right shift rescheduling and total rescheduling.	Experimental Data

Linear Programming. Further details on the methodologies discussed can be found in Table 10.

4.4. Parameters optimization

Optimally setting parameters in the manufacturing stage, including the optimal adjustment of machining parameters and production line settings, as well as optimizing parameters in the design stage—which is related to manufacturing—can significantly improve energy efficiency. Accordingly, this review investigates the proposed solutions for the Parameters Optimization challenge as presented in the literature across three categories: Machining parameters optimization, process parameters optimization, and design parameters optimization. Although the optimization of machining parameters could be included under the process parameters optimization category, it is addressed separately in this review. This separation is due to the fact that many papers specifically focus on either machining parameters or other production line parameters, prompting the classification of machining parameters optimization as a distinct subclass.

In the following sections, the proposed solutions for each subproblem are discussed in two subcategories: AI-based and AI-aided solutions. Generally, the use of an optimization technique, specifically GA, which are enhanced by AI algorithms to find optimal parameters, is the most widely used solution across all three subclasses. Typical input and output data include component, machine, line-level, and production-related data, with controlling variables at the machine and line levels.

4.4.1. Machining parameters optimization

In this subproblem, the focus is on optimizing settings in machining processes, such as feed rate, toward energy-efficient objectives. The research typically centers on identifying the most energy-efficient combinations of machining parameters.

To find the optimal machining parameters, the utilization of AI-based solutions, specifically RL, is only suggested by [76] and [77]. In [76], AC networks with a PPO-based optimizer are suggested for optimizing the cutting parameters of steel machining in the presence of changing tool wear. Similarly, in [77], the author utilizes AC networks to optimize the batch machining parameters while the tool wear undergoes dynamic changes.

In many papers, AI, specifically shallow ANNs architectures are suggested as an aid for the main decision-maker. The use of multi-layer ANN predictions for a GA optimizer is proposed by [78] and [79] for optimizing parameters of the milling process and the most energy-intensive operation in rotary impeller manufacturing, respectively. With a similar idea, but utilizing different optimization technique, the authors in [80] suggest the use of multi-layer ANN predictions to enhance parameters optimization of welding and machining processes, which is achieved by employing a Multi-Objective Evolutionary Algorithm based on Decomposition. In [81], an ANN and the LINMAP are suggested to improve the NSGA-II in optimizing the parameters of the steel machining process. To be more specific, an ANN, with one middle layer predictions are utilized to guide the optimizer, and LINMAP is applied to select the most preferable solution generated by the optimizer based on predefined criteria. In [82] and [83], ANNs, with one and two hidden layers are used to guide Design Expert software in optimizing parameters of steel CNC machining. Additionally, Response Surface Methodology is suggested to understand the interactions between different parameters and their impact on the machining process. For further insights into the methodologies discussed in the referenced articles, refer to Table 11.

4.4.2. Process parameters optimization

This subproblem encompasses a wider range of parameters within a production line, including temperature settings, material type selection, and other critical variables. A few existing papers, [84], [85], and [86], in this subclass propose the use of AI algorithms to support the GA optimizer. In [84], due to the superior accuracy of SVR compared to an ANN with one hidden layer containing nine neurons, its predictions are utilized to guide the GA in optimizing the parameters of the stabilization process in carbon fiber production. In [85], the authors propose using ANN, three hidden layers predictions to accurately inform and guide a GA in optimizing the parameters of the electrical discharge machining process, which utilizes waste cooking oil as a dielectric fluid. A similar solution to [85] is employed in [86] to find the optimal combination of dielectrics and electrode materials for the Electric Discharge Machining process. For additional insights into the methodologies discussed in the referenced articles, review Table 12.

4.4.3. Design parameters optimization

This subproblem focuses on designing energy-optimized manufacturing layouts, tools, and physical components of the machinery used in manufacturing processes. While [87] utilizes an AI-based solution, [88] and [89] apply it to support the main solution. To be more specific, In [87], the authors propose integrating ML techniques, experimental testing, and Virtual Reality visualization to design energy-optimal cutting tools, thereby optimizing milling operations.

Table 10
Resource Planning.

Literature	Objective	Input	Output	Controlling variables	Testbed
[61]	Energy cost and energy consumption	Machines' energy consumption state, buffer storage state, the current hour of the day and received electricity price.	Switching machines between operational and idle mode.	Same as the agent's action.	Simulation
[62]	Tardiness and energy consumption	Delivery time, loading and unloading position, battery state, current position and waiting time.	Assigning tasks and controlling battery replacement.	Same as the agent's actions.	Simulation
[63]	Energy consumption	Feed rate, spindle speed, cutting depth, energy.	Energy consumption.	Assigning jobs to the idle machines.	Experimental Data
[64]	Total tardiness and energy consumption	Solution distance and hypervolume.	Selecting a suitable heuristic operator for population evaluation, from the local search operators, such as reverting operator and intelligent algorithms, such as Multi-Objective Cuckoo algorithm.	Assigning Tasks, including pick up operation, delivery operation or pick and delivery operations in a single trip to AGVs.	Simulation
[65]	Energy cost	Historical data of real-time electricity price.	One hour ahead real-time electricity price.	Turning machines on/off.	Simulation

Table 11
Task allocation and Resource planning.

Literature	Objective	Input	Output	Controlling variables	Testbed
[66]	Total part manufacturing energy consumption and time.	GCN: Nodes, representing process planning elements like operations, features of nodes, representing specific attributes relevant to the process planning, such as energy consumption, edges, representing the relationships or flows between these elements, and adjacency Matrix, representing the connectivity between nodes. State-space: Candidate nodes, immediate graph, and joining node.	GCN: Compressed representation of the input graph. Action: Node selection.	Selection of operation (milling and drilling), machine and cutting tool and sequencing between operations.	Experimental Data
[67]	Energy consumption and production time.	State-space: Prior operation and the condition of operations, machine, and cutting tools. Actor network: States. Critic network: State-action pairs.	Actions: Continuous actions include cutting speed, feed rate and cutting depth and cutting width. Discrete actions involve combinning different machining resources. Actor network: Probability of choosing each possible action. Critic network: Predicted value function.	Same as the agents' actions.	Experimental Data
[68]	Total energy consumption	a 4-bit binary number, representing the performance of the subswarms, where 0 means bad and 1 means good.	Increasing or decreasing the size of each sub-swarm.	Sequence of Job, selection of the machines, speed level control, machine on/off control.	Experimental Data

Table 12
Machining parameters optimization.

Literature	Objective	Input	Output	Controlling variables	Testbed
[69]	Specific energy of the machining process, production time of the machining process	State-space: Tool wear rate, previous step energy, production time, and production cost. Actor network: States. Critic network: State-action pairs.	Actions: Selection of cutting tool, cutting speed, and cutting depth. Actor network: Probability of choosing each possible action. Critic Network: Predicted value function.	Sam as the agent's action.	Experimental Data
[70]	Completion time and energy consumption	State-space: Workpiece diameter, machining allowance, and tool wearing condition. Actor network: States. Critic network: State-action pairs.	Actions: Selection of cutting tools, cutting speed, feed rate, and cutting rate. Actor network: Probability of choosing each possible action. Critic network: Predicted value function.	Same as the agent's actions.	Real-world
[71]	Energy consumption	Spindle rotational speed, feed rate, depth of cut and number of teeth.	Total specific energy and energetic efficiency.	Spindle rotational speed, feed rate, depth of cut and number of teeth.	Experimental Data
[72]	Specific energy consumption and surface roughness	Stepover, depth of cut, feed per tooth, and cutting speed.	Specific energy consumption and surface roughness.	Stepover, depth of cut, feed per tooth, and cutting speed.	Experimental Data
[73]	Energy consumption, greenhouse gas emissions, hazardous liquid wastes, production costs, processing time, resource utilization, and product quality	Machining process: Cooling, diameter, cutting edge, speed rate, feed rate and the depth of cut. Welding process: The current time and cycle of time.	Machining process: Roughness, cutting cost, machining duration and energy consumption. Welding process: Indentation, diameter, energy consumption and processing time.	Same as the output.	Experimental Data
[74]	Surface roughness, material removal rate and energy cost, including energy consumption cost	Cutting speed, depth of cut, and feed rate.	Surface roughness and power consumption.	Cutting speed, depth of cut, and feed rate.	Experimental Data
[75]	Tool-chip interface temperature, specific energy consumption, yield strength, and percentage elongation	Speed, feed rate and cutting depth.	Tool-chip interface temperature, specific energy, yield strength, and percentage elongation.	Machining Speed, feed rate and cutting depth.	Experimental Data
[76]	Energy consumption	Cutting speed, feed rate, and depth of cut.	Energy consumption and energy efficiency.	Cutting speed, feed rate, and depth of cut.	Experimental Data

Bagging of MLPs is chosen as the most accurate model compared to others, such as RFs Ensembles, and is utilized to predict tool performance under various conditions. Based on the predictions, an iterative optimization process is applied to refine energy-efficient tool geometries and machining settings. This optimization process is further supported by Virtual Reality visualization, which facilitates interactive exploration of the effects of different parameters on energy use. In [88], the integration of a Multiple Linear Regression model with a deep NN is proposed to assess PSO toward energy-efficient designs in cyber-physical production systems at the component level. In [89], the author proposes the integration of a TBRFFNN, CRITIC, and Desirability Approach for optimizing nozzle design parameters in diamond burnishing operations. The strategic combination of predictive insights from TBRFFNN and importance ratings obtained from CRITIC enables Desirability Approach to drive the optimization process. To gain further understanding of the methodologies covered in the referenced articles, see Table 13.

5. A conceptual EE-DT framework

In recent years, DT technology has emerged as a crucial component of intelligent manufacturing, driven by its ability to enhance operational efficiency and decision-making [90,91]. The primary concept of DT in manufacturing involves creating a high-fidelity digital replica of the physical manufacturing space—including devices, tools, and components—that interacts in real-time and bidirectionally with the physical space to enhance decision-making processes [92]. Specifically, a DT serves as an intermediary system architecture. On one side, it simplifies and organizes data from the physical environment, accurately representing the status and performance of physical entities for analysis and visualization in the digital domain [93,94]. On the other side, it translates abstract intelligent control solutions from the digital realm into practical real-world applications, effectively bridging the gap between the digital and physical worlds [95,96].

Fig. 11 illustrates the three essential components for developing a DT: Information Model, Communication, and Data Processing. Standard pre-defined information models are used to describe and represent manufacturing physical objects effectively. The communication network synchronizes the physical components with their digital counterparts, ensuring timely data transmission and real-time reactions whenever sensors detect a state change. Data Processing, the focus of this review, includes data pre-processing, which serves as the foundation for monitoring and prediction, while monitoring and prediction, in turn, form the basis for data-driven decision-making. The data pre-processing block encompasses several key tasks: data cleansing to address noise and missing data, data storage to create a training pool for decision-making, and stream processing handling to ensure low-latency data processing.

The DT approach has been extensively utilized in various studies as a tool for the real-time implementation of solutions aimed at achieving energy-efficient manufacturing systems. For instance, several researchers, including [97] and [98], have suggested DT for energy modelling purposes. Additionally, DT has been employed in energy-efficient optimization, with [99] focusing on process parameters and [100] on machining parameters. The approach has also been explored for energy-efficient scheduling; [101] discusses its application in task scheduling, while [102], [103], and [104] examine its use in resource scheduling. Moreover, DT has been applied to real-time energy consumption-based control, as highlighted in studies such as [105], [106], [107], [108], and [109]. Additionally, [110] investigates the use of DT for real-time energy price-based control.

While energy efficiency challenges are a fundamental aspect of manufacturing systems, reviewing findings from various research works reveals that AI offers a promising solution for addressing these challenges. In this context, the DT concept can be an asset in bringing abstract AI driven solutions to the real-world for solving energy efficiency challenges in manufacturing systems. The DT integration for implementation of abstract AI-driven solutions in real-world has been proposed by only two papers ([32] and [33]) for Monitoring and Prediction and has not been proposed by any papers for decision making related challenges. Accordingly, proposing a comprehensive DT supported framework that integrates energy efficiency challenges with AI approaches in manufacturing systems can be beneficial for academia, future research directions, and industry practitioners.

Fig. 12 presents the framework developed in this paper, named EE-DT, based on the findings of the reviewed papers and the authors' insights. Generally, the proposed conceptual framework consists of two main layers: the Physical Layer and the Digital Layer, collectively known as the Energy-Focused DT. The arrows in the figure represent the flow of data between these layers. To clarify the meaning of the arrows, the green arrow represents informational data. This data includes feedback such as system status, performance metrics, and other details that provide insights or are used for analysis. Essentially, this information flows from the system to the digital layer, enabling a better understanding of the manufacturing process.

The other arrows represent commands, which are instructions or directives that trigger specific actions within the system. The red arrows represent scheduling commands, ensuring tasks are completed in a timely manner. The gray arrows signify Real-Time Control commands, which are used to manage immediate operational adjustments. Finally, the blue arrows represent Parameter Optimization commands, directing adjustments to optimize system parameters for improved performance. Each type of command is sent to a specific area of the manufacturing system to ensure smooth and efficient operation. To the best of the authors' knowledge, this is the first comprehensive framework that aims at addressing energy efficiency challenges in manufacturing systems using AI and DT concept.

The contributions of this framework can be listed as below:

1. Comprehensive Energy Efficiency Objective Block:
   The framework proposes a comprehensive energy efficiency objective block encompassing all possible energy-related objectives, which can be integrated with AI-driven solutions to enhance energy efficiency in manufacturing systems. This block addresses both established approaches from existing literature and novel methodologies introduced in this paper to systematically improve energy efficiency.
2. Novel Integration of AI-Driven Data Analysis and Decision-Making:
   The framework represents a novel integration of AI-driven data analysis solutions with AI-driven decision-making solutions, aimed at addressing prevalent energy efficiency challenges in manufacturing systems.

Table 13
Process parameters optimization.

Literature	Objective	Input	Output	Controlling variables	Testbed
[77]	Energy consumption	Temperature, space velocity, stretching ratio, fiber density.	Predicted density of the oxidatively stabilized polyacrylonitrile fiber.	Temperature, space velocity, stretching ratio.	Experimental Data
[78]	Specific energy consumption, surface roughness, material removal rate	Powder concentration, surfactant concentration and treatment types, including single cryogenic treatment and double cryogenic treatment.	Specific energy consumption, surface roughness, material removal rate.	Powder concentration, surfactant concentration and treatment types, including single cryogenic treatment and double cryogenic treatment.	Experimental Data
[79]	Productivity, quality, power consumption	Dielectric type and electrode material.	Tool wear ratio, surface roughness, dimensional deviation, specific energy consumption.	Selection among six bio-degradable dielectrics and choice among four different electrodes materials.	Experimental Data

Table 14
Design parameters optimization.

Literature	Objective	Input	Output	Controlling variables	Testbed
[80]	Energy consumption	Cutting conditions: Feed per tooth and revolution, feed rate, spindle speed, cutting speed, axial depth of cut. Tool geometry: Number of teeth, helix angle, amplitude of sinusoid, wavelength of sinusoid, serrated tool profile, tool identifier. Cutting force measurements in X, Y and Z directions and total cutting force.	Power consumption due to the cutting process.	Cutting conditions, and tool geometry.	Real-world
[81]	Energy consumption	Maximum velocity, maximum acceleration,	Energy consumption	Maximum velocity, maximum	Real-world

Table 15
Design parameters optimization.

Literature	Objective	Input	Output	Controlling variables	Testbed
		motion time, position, and distance.		acceleration, motion time, position, and distance.	
[82]	Energy efficiency, the total height of profile roughness and noise emission.	Inner diameter, spraying distance and pitch angle.	Energy efficiency, the total height of profile roughness and noise emission.	Inner diameter, spraying distance and pitch angle.	Experimental Data

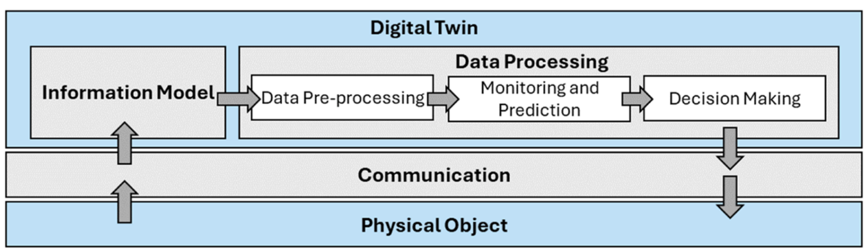

Fig. 11. Schematic representation of a DT system.

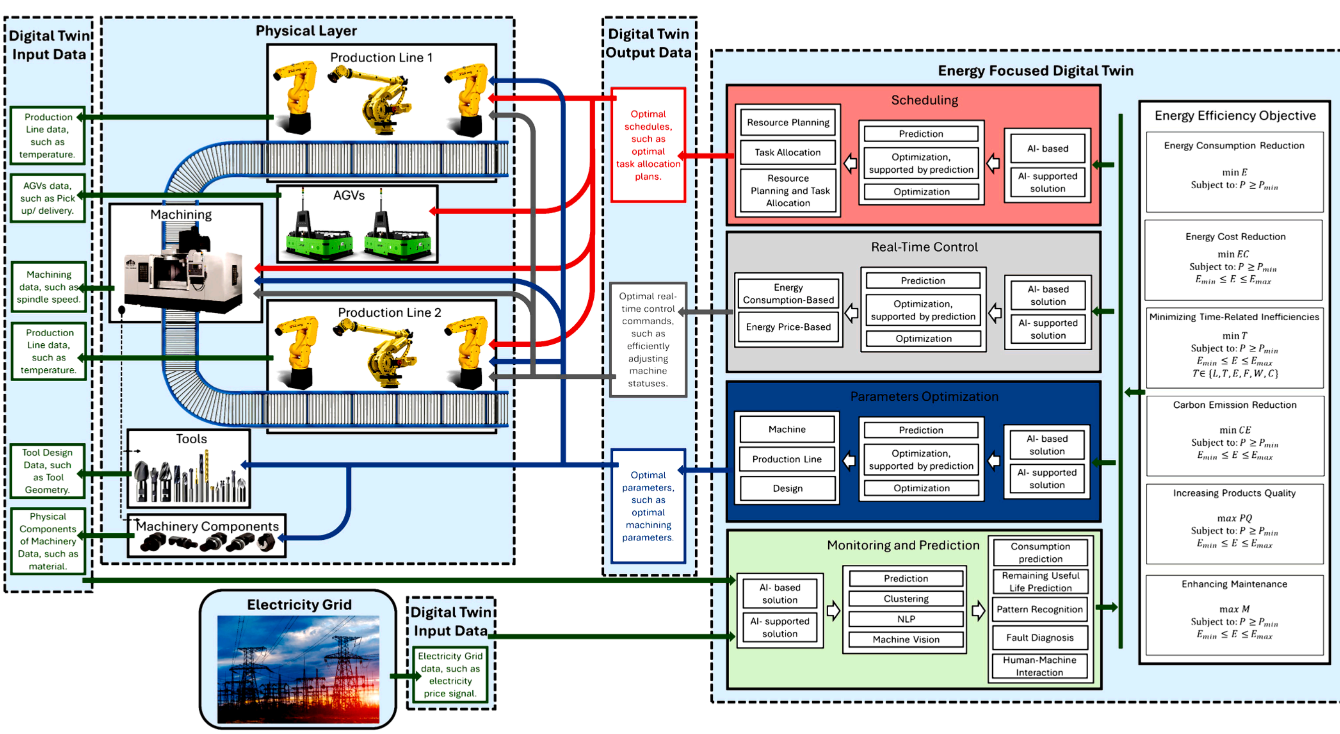

Fig. 12. A Conceptual EE-DT Framework.

3. Comprehensive AI Solutions for Both Data Analysis and Energy Optimization:
   The framework demonstrates how AI applications can be used to solve data analysis-related challenges, including Monitoring and Prediction, and energy optimization-related challenges, involving Parameters Optimization, Real-Time Control, and Scheduling.
4. Flexible Configuration Structure for the Digital Side:
   The framework develops a flexible configuration structure for the digital side, based on common energy efficiency challenges, AI-driven solutions, and possible energy efficiency objectives.
5. Real-Time Optimization of the Physical Layer:
   The framework demonstrates opportunities for energy efficiency within the physical layer and outlines the optimal commands from the digital layer aimed at achieving energy efficiency objectives.
6. Comprehensive Output Data for Achieving Energy Efficiency Objectives:

The framework specifies the output data from the physical layer that are relevant and useful for achieving energy efficiency objectives.

Physical layer.

The physical layer represents a sample manufacturing system that includes two production lines equipped with robotic arms, a machining center, and AGVs. The typical output data from this physical layer can be categorized into three levels: component-level data, machine-level data, and line-level data.

- Component-level data pertains to machinery components and tools.
- Machine-level data involves data related to the machining process, such as cutting speed.
- Line-level data covers the status of production line equipment, including machines and buffers, process parameters such as temperature, and production-related data such as output volume.

The data from these levels, along with electricity grid data, serve as inputs for the DT. This comprehensive data collection ensures that the DT has a holistic view of the manufacturing process.

5.1. Energy-focused DT

The energy-focused DT part consists of five main blocks. Four of these blocks handle different energy efficiency challenges in manufacturing systems: Monitoring and Prediction, Real-Time Control, Scheduling, and Parameters Optimization. The fifth block, Energy Efficiency Objectives, represents various optimization goals aimed at improving energy efficiency. In the mathematical equations providing in this block C is makespan, CE is carbon emissions, E is energy consumption, EA is Earliness, EC is energy cost, F is Flow Time, L is Lateness, M is maintenance, P is productivity, PQ is product quality, T is tardiness, and W is waiting Time.

The input data to the DT first feeds into the Monitoring and Prediction block, forming the basis for addressing decision-making challenges (Real-Time Control, Scheduling, and Parameters Optimization). The results of this analysis, combined with specific energy efficiency objectives, guide the decision-making processes in the related blocks. The outputs from these blocks, including optimal scheduling plans, control commands, and parameters adjustments, are fed back into the physical layer's equipment.

Each energy efficiency block consists of three types of subblocks:

1. Sub-problems (on the left side of the section): These blocks present the specific sub-problems associated with each energy issue.
2. AI approaches (on the right side of the section): These blocks showcase possible ways to use AI as solution to address the sub-problems.
3. Application of AI (in the middle of the section): These blocks represent how AI approaches can be applied to solve the sub-problems.

The proposed conceptual EE-DT framework integrates AI solutions into the energy-efficient manufacturing system, providing a structured approach to address energy efficiency challenges. This framework highlights the interaction between physical manufacturing components and advanced digital analytics, aiming to enhance energy efficiency. The following research challenges section will address the challenges and opportunities related to implementing this framework.

6. Research challenges

The proposed conceptual EE-DT framework in the previous section provides a comprehensive solution for utilizing AI-driven approaches in energy-efficient manufacturing systems. In the following section, we identify and discuss the four major critical research challenges within this domain. These challenges include defining the objectives for energy efficiency, identifying energy-saving potentials, dealing with the issues arising from energy data collection, and implementing AI approaches in real-world scenarios. Each of these challenges is examined in detail in the subsequent sections.

6.1. Defining objectives for energy efficiency

To provide valuable insights for future research on energy-efficient manufacturing systems and improve their comparability, it is essential to define both direct and indirect objectives influencing energy efficiency. Energy consumption remains a direct objective, while energy cost is treated as an indirect objective frequently cited in the literature. Reducing energy consumption while maintaining productivity clearly enhances energy efficiency. However, when focusing on energy cost reduction, it is crucial to impose constraints on energy consumption to ensure that energy efficiency is not compromised. These constraints include adhering to the minimum energy requirements for manufacturing equipment, maintaining the maximum allowable energy usage set by the electricity grid or equipment manufacturer, and ensuring that productivity levels are sustained. By optimizing energy usage in response to energy price signals (e.g., using energy during off-peak hours), energy cost can be minimized without increasing overall energy consumption, thereby driving improvements in energy efficiency.

Other direct and indirect objectives that can also enhance energy efficiency and should be prioritized in future research include:

- Reducing carbon emissions: Reducing carbon emissions can directly reduce energy consumption, thereby improving energy efficiency. However, it is crucial to ensure that carbon emission reduction measures do not compromise productivity.
- Reducing carbon emissions:

6.2. Direct objective (when green energy is unavailable)

In the absence of green energy sources, focusing on reducing carbon emissions can directly reduce energy consumption, thereby improving energy efficiency. However, it is crucial to ensure that carbon emission reduction measures do not compromise productivity.

- Indirect Objective (when green energy is available):

Utilizing green energy sources while adhering to the required minimum and maximum thresholds of energy consumption and maintaining productivity can not only reduce the carbon footprint but can also be considered a method for improving energy efficiency. In this scenario, reducing carbon emissions indirectly impacts energy efficiency when green energy is available.

- Reducing time-related inefficiencies: There is no direct correlation between reducing time-related inefficiencies—such as lateness, tardiness, earliness, flow time, waiting time, and makespan—and reducing energy consumption. Nevertheless, if efforts to reduce these inefficiencies consider the minimum and maximum energy consumption thresholds while maintaining productivity, energy efficiency can be improved.
- Increasing product quality: While there is no direct relationship between increasing product quality and reducing energy consumption, improving product quality within the constraints of minimum and maximum energy consumption, and without compromising productivity, can enhance energy efficiency.
- Enhancing maintenance practices: There is no direct link between enhancing maintenance practices and reducing energy consumption. However, if maintenance improvements are implemented within the bounds of minimum and maximum energy consumption and do not affect productivity, energy efficiency can be improved.

Accordingly, a key question for future research direction would be, how will the integration of AI algorithms with these newly defined energy-saving objectives impact energy-saving practices, and which objective is expected to result in the greatest energy savings in manufacturing systems?

6.3. Identifying energy saving potentials

Identifying energy-saving potential in manufacturing systems is essential for developing effective strategies that target the most energy-critical areas. The following key aspects should be prioritized to fully leverage the potential for energy savings:

1. **A manufacturing system level, specifically Process-Related Elements**: it involves identifying manufacturing levels, including component, machine and line level and more specific process-related elements, involving machining parameters, process parameters, production line's equipment statues, machinery components design parameters and tools' wear status with substantial energy-saving potential. Accordingly, a key question for future research direction would be which of a manufacturing systems' level, more specific a manufacturing system element have more potential for energy efficiency practices?
2. **Energy Efficiency challenge:** it focuses on identifying the most influential challenges to energy efficiency in manufacturing systems, encompassing areas like Monitoring and Prediction, Scheduling, Real-Time Control, and Parameters Optimization, to ascertain which factors most significantly impact energy consumption. Accordingly, a key question for future research direction would be which of the energy efficiency challenges have more potential for energy efficiency practices?
3. **Solution:** it underscores the importance of conducting comparative research on the efficacy of AI-based solutions versus traditional non-AI approaches, particularly metaheuristics. The study has reviewed multiple cases where AI techniques have been integrated with metaheuristics, such as GA and NSGA-II, demonstrating superior results. This highlights the potential of traditional approaches in tackling energy efficiency challenges within manufacturing systems. Therefore, it is crucial to rigorously assess the performance of these conventional algorithms and benchmark them against AI-based solutions to identify the most effective methods for achieving energy-efficient manufacturing. Accordingly, a key question for future research direction would be which of the AI-based solutions versus traditional non-AI based approaches have more potential for energy efficiency practices?

Concentrating on these aspects will facilitate the identification and implementation of the most impactful strategies for enhancing energy efficiency in manufacturing systems.

6.4. Dealing with issues arising from energy data collection

The effective deployment of AI-driven solutions in energy-efficient manufacturing systems necessitates extensive high-quality data on energy consumption and influencing factors. To facilitate this, the implementation of sensors is essential. However, sensor installation can be prohibitively expensive, and manufacturers may be hesitant to deploy a large number of sensors on their equipment or to share comprehensive data due to privacy concerns. Consequently, there is a pressing need for future research to focus on the challenges arising from energy data collection, which are often overlooked in the existing literature that depends on pre-existing datasets.

Among the reviewed studies, only two have explicitly addressed the costs associated with data collection and the preservation of data privacy by employing Transfer Learning and Non-Intrusive Monitoring techniques. Unsupervised learning methods, which have been less frequently explored in the reviewed literature, offer potential solutions to simultaneously address data collection and privacy preservation challenges. These algorithms do not require labeled training datasets, thereby partially mitigating the data acquisition problem. Nevertheless, it is important to acknowledge that unsupervised methods may not achieve the same level of accuracy as supervised methods in the context of energy data analysis or the operational efficiency of RL approaches in decision-making contexts. Accordingly, a key question for future research direction would be How can cost-effective, privacy-preserving, and accurate energy data collection methods, such as unsupervised learning, Transfer Learning, and Non-Intrusive Monitoring, be integrated into AI-driven energy optimization systems to address the challenges of data availability and quality in manufacturing systems?

6.5. Implementing AI approaches in real-world scenarios

Out of the 65 AI methodologies analyzed across various articles, only 12 have been validated in real-world scenarios. Notably, despite approximately one-third of these methodologies addressing scheduling problems, none have been validated in an online mode. The primary reason for this lack of validation in real environments is the significant challenges posed by online implementation. Below, we outline the key challenges and potential future research directions to address them.

6.5.1. Adapting AI algorithms to dynamic manufacturing environments

One of the most common challenges across all AI branches is the necessity to adapt trained algorithms to new and evolving situations. This challenge requires continuous updates to ensure that AI systems can adjust to real-time changes in the manufacturing environment. However, designing cost-effective, privacy-preserved, and secure updating mechanisms is complex, especially in scenarios where the algorithm needs to respond quickly to sudden shifts. Therefore, future research could focus on developing adaptive algorithms that are capable of responding to dynamic changes in the manufacturing environment. One example is investigating Federated Learning (FL) models that allow locally trained models to be transferred instead of raw data, reducing communication costs and preserving privacy. A potential research question could be: How can methods like FL be leveraged to enhance the adaptability of AI models in real-time manufacturing environments? Additionally, the integration of human operators into this updating process could help mitigate delayed responses. Future studies could also explore: What role can human operators play in collaborating with AI systems to ensure real-time decision-making during unexpected changes?

6.5.2. Addressing the black-box nature of AI for better interpretability

Another significant challenge is the black-box nature of AI models, which makes it difficult to interpret how decisions are made, thereby reducing trust and reliability in real-world applications. This issue is especially critical in high-stakes environments like manufacturing, where the reliability of AI-driven decisions is important. To address this, future efforts could focus on developing explainable AI models that provide transparency in decision-making. For example, researchers could work on creating AI models that can explain their decision-making process in real-time to operators. A specific research question might be: How can explainable AI techniques improve the reliability and trustworthiness of AI systems in industrial applications? Additionally, integrating humans into the AI-based decision-making process could also offer a solution by allowing for oversight and intervention where necessary. Researchers could also explore: How can human-AI collaboration be designed to enhance decision-making in complex manufacturing systems?

6.5.3. Overcoming challenges in RL deployment

RL presents several unique challenges when applied to manufacturing. The first challenge is the lack of comprehensive and realistic simulation environments for RL training. There is currently a shortage of Application Programming Interfaces (APIs) that can provide robust, simulated manufacturing environments where RL agents can be trained. To address this, future research could focus on developing APIs that simulate realistic manufacturing environments for RL training. Another key challenge is transferring RL agents trained in virtual environments to real-world settings. If the training environment does not accurately reflect the complexities of a real-world manufacturing environment, the RL agent may perform poorly when deployed. DTs can be a solution to make virtual environments close to real environments. Therefore, DT can help to address this issue by creating more realistic virtual environments for RL agents to train in. A relevant research question in this context is how DTs can be enhanced to better simulate real-world conditions for effective training of RL agents in manufacturing environments. Lastly, the trial-and-error nature of RL poses safety risks when applied to real-world scenarios, particularly in manufacturing where mistakes can be costly or dangerous. Research into developing safe exploration strategies is essential to ensure that RL agents can learn effectively while minimizing risks during their deployment. A crucial research question in this area is what safe exploration strategies can be implemented to reduce risks during the deployment of RL in industrial environments while ensuring effective learning.

7. Conclusions

Over the last decade, research on energy-efficient manufacturing has surged with the rapid development and application of various Industry 4.0 technologies. However, there are few review articles addressing the evolution of energy-efficient manufacturing systems within the context of AI. To better understand the current utilization of AI in addressing energy efficiency challenges in manufacturing systems, this paper proposes a SLR from 2013 to 2024 that combines both bibliometric and qualitative analyses to answer the four research questions proposed in Section 2.

The primary scientific contributions of this paper are outlined as follows.

- Firstly, bibliometric analysis is employed to quantitatively analyze research trends and focus areas of AI for energy-efficient manufacturing systems. Some of the more important results derived from this analysis are: a growing trend in the utilization of AI for improving energy efficiency in manufacturing systems, and two significant shifts over the last decade. The first shift is from focusing on the utilization of AI for data analysis challenges, such as Monitoring and Prediction, to applying AI for decision-making-related challenges, including Scheduling, Real-Time Control, and Parameter Optimization. The second shift is from the use of NNs and classical ML algorithms to advanced approaches, such as DL and DRL. Moreover, a significant gap was identified in the studies, as there is limited validation of the proposed AI solutions in real-world scenarios.
- Secondly, a qualitative review of existing literature on the topic is presented. The commonly focused energy efficiency challenges in manufacturing systems are identified, and the proposed AI-driven solutions from various studies to address these challenges are summarized in detail and compared.
- Third, we propose a novel conceptual EE-DT framework to facilitate implementation of the AI solutions to solve energy efficiency challenges in manufacturing systems.
- Finally, major research issues and challenges are identified and discussed, highlighting future research directions for AI for energy-efficient manufacturing systems.

In addition to its scientific contributions, this study has substantial practical implications. The review results could assist manufacturers in comprehending cutting-edge research on AI and manufacturing systems in academia, identifying gaps between academic research focuses and practical industrial development, and integrating Industry 4.0 technologies, such as AI, into their manufacturing processes for efficiency enhancement objectives, such as energy-efficient manufacturing systems.

It is important to acknowledge that a limitation of this study is the exclusive reliance on the Scopus database for the collection of publication data. While Scopus is one of the largest and most reputable academic databases, it may not encompass all relevant publications, potentially leading to a fraction of literature being overlooked. We aspire that this work will assist both researchers and industrial practitioners in gaining a comprehensive understanding of the current state of research on AI for energy-efficient manufacturing systems. Furthermore, we hope it will inspire new ideas for the development of energy-efficient manufacturing systems in the era of Industry 4.0.

CRediT authorship contribution statement

Yuchun Xu: Writing – review & editing, Supervision, Resources. **Youxi Hu:** Writing – review & editing, Visualization. **Ming Zhang:** Writing – review & editing, Validation. **Chao Liu:** Writing – review & editing, Visualization, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Mohammad Mehdi Keramati Feyz Abadi:** Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization.

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.

Acknowledgement

The authors wish to acknowledge the funding support from the Royal Society Research Grant (RGS\R1\231109), the Royal Society International Exchanges Cost Share (NSFC) Grant (IEC\NSFC\223198), and the National Natural Science Foundation of China (52105534).

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