Artificial Intelligence for Smart Grids in Smart Manufacturing

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Smart manufacturing is not only beneficial to optimize product manufacturing processes with minimum costs, but also conducts product life cycle management to reduce energy consumption. Sustainable and smart manufacturing involves improving the efficiency and environmental sustainability of various manufacturing operations such as resource allocation, data collecting and monitoring, and process control.

Keywords: smart grid ; artificial intelligence ; optimization techniques ; smart manufacturing

1. Introduction

Since the concept of Industry 4.0 was proposed, manufacturers have actively introduced the latest technologies such as the Internet of Things (IoT), artificial intelligence (AI), big data, machine learning, blockchain, edge computing, 5G, drone applications, AR/VR, and cyber-physical systems into manufacturing processes and operations [1]. Smart manufacturing is not only beneficial to optimize product manufacturing processes with minimum costs, but also conducts product life cycle management to reduce energy consumption [2]. In smart manufacturing, the IoT collects data, including the input/output data and parameters (or recipes) for manufacturing equipment, workforce-related data, and work environmental conditions. Then, based on the data, the AI and optimization techniques are further developed to provide intelligent decisions and actions to improve the manufacturing processes and operations while optimizing some objectives, e.g., minimizing production costs and energy consumption. Recently, manufacturers have paid increasing attention to achieving net zero carbon emissions by 2050. Under uncertain energy demand, manufacturers control intermittent energy generation and usage time, as well as long-term operation planning, and must develop economical designs and smart resource utilization of micro-grids to achieve net-zero energy operations [3]. Therefore, there is of urgent need for manufacturers to effectively implement manufacturing resource allocation (including energy data and equipment resources), manufacturing data monitoring (including big data collection and analysis), and manufacturing process control (including energy usage and cost control) to achieve the goal of sustainable and smart manufacturing.

There are requirements for continuously developing novel technologies and sustainable environments, therefore, manufacturers rely increasingly on electricity and require a smart, efficient, and reliable energy management system. As a solution, the smart grid (SG) replaces the existing electrical grid to effectively adjust and distribute energy according to demand [4]. Generally, the SG is integrated with renewable energy (e.g., solar, wind, and geothermal energy) to provide clean, sustainable, efficient, and reliable energy sources, allowing manufacturers to have better choices for energy planning in manufacturing processes. As shown in **Figure 1**, the SG provides a platform for energy supply using the latest technologies (including communication technologies, information provision, cybersecurity, and computational intelligence) to demonstrate various characteristics, including self-healing, flexibility, prediction, interaction, optimization, and security [4]. The application areas of SG have existed not only in life, but also widely in different industries. Dileep [5] investigated SG technologies and their applications that provide two-way power systems in industrial applications, electric vehicles, home buildings, intelligent electronic devices, and local area networks. Babayomi et al. [6] reviewed distributed energy resources applications as well as control prediction in wind energy conversion systems, solar photovoltaics, fuel cells, and energy storage systems. Bhattarai et al. [7] provide an energy transformation solution of SG for various industries for strengthening the power system, integrating renewable sources, electrifying the transport sector, and harnessing bioenergy.

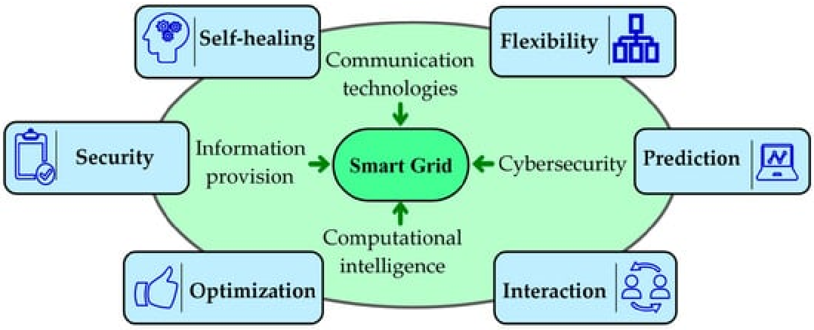

Figure 1. Major technologies and characteristics of smart grids [4].

However, as the power market has become increasingly free and open, more diversified energy sources are integrated into the SG, which increases the complexity of transmitting and distributing energy. Over time, such an increasing interconnection scale makes the SG system more complex than the previous systems. Therefore, it has been important and unavoidable to investigate how to maintain a stable energy supply through the SG system. Recently, the applications of AI technologies have been used to analyze and control the stability of the SG and provide effective smart solutions for complex systems, and they have received enormous attention [8]. The recent applications of AI technologies in power systems have mainly included fault detection and diagnosis, energy planning, energy forecasting, and power system optimization (e.g., economic scheduling, power optimization process and problem formulation, optimization of neural network applications, and reactive power optimization) [9].

2. Overview of SG Operations for Smart Manufacturing

2.1. Distribution Side Management through SGs

The centralized power generation and one-way power distribution of conventional electrical grids cause problems of excessive energy loss and uneven distribution. The SG makes the controlled electrical network more automated and more effective by installing smart measures and monitoring equipment so as to achieve more efficient, reliable, and environmentally friendly electricity distribution. Recent instances on the distribution side management of electrical grids through SGs are reviewed as follows. Xia et al. [10] proposed a cyclic neural network with stacked gated cyclic units for single-variable and multi-variable actual situations to effectively control and manage the grid. For smart power control and saving, Khalid et al. [11] proposed a multivariate neural network model for demand forecasting and electricity price estimation, and showed that their overall accuracy was higher than other univariate forecasting methods. To effectively control electricity demand, Avancini et al. [12] installed smart meters to provide measurement, communication, control, display, and synchronization functions, and established a smart energy network that can be effectively managed. To effectively reduce energy demand and carbon emissions, Jaiswal and Thakre [13] adopted the control and management of smart meters in the SG based on detailed electricity consumption and price information to plan the energy use. Yang et al. [14] established an energy-saving and reliable SG by installing smart meters in the power system, analyzing the actual power consumption data, and introducing probabilistic load forecasting to better control the uncertainty and volatility of future demand. Shi et al. [15] considered a complex SG system integrated with solar power and renewable energy and provided an AI solution for the stability analysis and control of solar power generation.

2.2. Demand Side Management through SGs

With a limited power supply, the demand side uses SG technologies to calculate, manage, and allocate power usage for various manufacturing and operational needs. The previous works on demand side management strategies are reviewed below. Bagdadee et al. [16] combined the intelligent industrial power framework with manufacturing machines to collect their power consumption data, and carried out demand management according to the actual needs of consumers. Bahaghighat et al. [17] proposed machine learning algorithms and visual sensor network approaches to forecast wind power generation in SGs to improve their performance and efficiency. When facing the demand of dynamic power changes, under the SG following the cyber-physical system model, Alazab et al. [18] proposed a multi-directional long-short-term memory to establish a stable predictive technology to predict the stability of the SG network, which is more effective than conventional machine learning models. For renewable energy incorporated into the SG, Mostafa et al. [19] proposed a five-step method based on the energy Internet to collect big data for predicting the stability of SG. To manage and reduce the overload of the SG system, Santo et al. [20] adopted AI and optimization strategies to establish an effective demand-side decision-making management system to effectively control energy costs.

2.3. Smart Manufacturing Using Distribution and Demand Side Management through SGs

Based on the distribution and demand side management of SGs, as well as the classification of SG technologies (i.e., communication technology, information provision, computing intelligence, and cybersecurity in **Figure 1**), the related works on the applications of SGs using various techniques are classified in **Table 1**. Neural networks [10][11][21], smart meters [12][13][14][22], and artificial intelligence [15] were adopted for power control; cyber-physical systems [18][23][24], big data [16][19][25], machine learning [17][18][26], AI [20][27] were adopted for demand side management, and network security [28][29][30][31][32] was used for communication and information transmission. All of them were implemented in smart manufacturing applications.

Table 1. Related works on the applications of SGs using various technologies.

Category	Technology	Application	Reference
Communication technologies	Cyber-physical system	Predicting stability	[18][23][24]
Information provision	Smart meter	Power generation and distribution, power sector, forecasting	[12][13][14][22]
	Big data	Power load management, predicting stability	[16][19][25]
Computational intelligence	Neural network	Power load, forecasting	[10][11][21]
	Machine learning	Power demand, forecasting, predicting stability	[17][18][26]
	AI	Predicting stability, power load management, power demand management, forecasting	[15][20][27]
Cybersecurity	Cybersecurity	Security of Internet operations	[28][29][30][31][32]

In the realm of smart factories, which integrate machinery, personnel, and equipment in the Industrial Internet of Things (IIoT), along with interconnected communication and computing networks, the importance of network security technology is heightened. This technology serves the crucial roles of identifying and safeguarding against potential information risks within the operational networks, as well as facilitating network restoration when required. Key applications in this domain involve the implementation of secure and dependable Advanced Metering Infrastructure (SRAMI) [28] and Information and Communication Technology (ICT) [32]. These applications are instrumental in addressing concerns related to data transmission reliability and security.

Two-way authentication mechanisms play a vital role in ensuring the security of information exchanges between the SG and users [29]. Additionally, assessing system risks within the physical infrastructure of SG networks [30][31] is an integral part of maintaining their robustness and security. Note that smart manufacturing and smart factories are central to the technological shift towards Industry 4.0. Utilizing AI technology for data analysis and enhancing the automation of network entities is an essential and inherent aspect of this transformation. Further details regarding these concepts will be expounded upon in subsequent sections.

3. AI Applications for SGs in Smart Manufacturing

This section firstly introduces the basic AI concept and then shows recent AI applications for SGs in smart manufacturing.

3.1. Basic Concept of AI

The concept of AI was first proposed by A. M. Turing in 1950 [33] to establish intelligent programs or equipment to develop good capabilities in self-learning, reasoning, self-correction, and so on. The AI technologies include the following abilities [34]: (1) the reasoning ability to solve problems, (2) the intellectual ability to represent and understand, (3) the ability to set plans and achieve goals, (4) the ability to understand language and communications, and (5) the ability of perceiving sound and image inputs and converting them into usable information.

As shown in **Figure 2** [35][36], an AI system generally consists of four modules: (1) data input, (2) processing algorithm, (3) output decision, (4) and knowledge database, in the same way as human beings think and make decisions. The four modules are operated as follows:

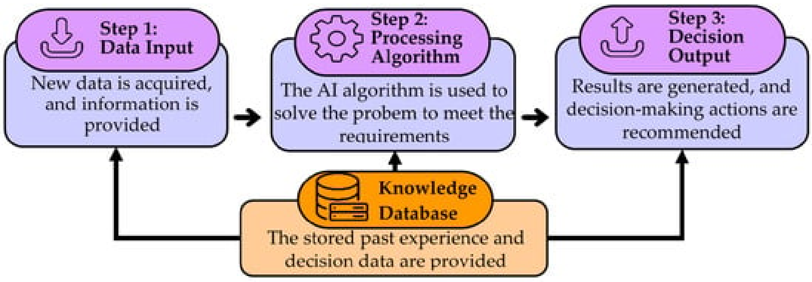

Figure 2. Flowchart of operating an AI system [35][36].

- Step 1 (data input): The input data is categorized into structured data (e.g., texts and numbers) or unstructured data (e.g., images and voice), depending on which physical sensors or devices (e.g., detectors and meters) are used in the system to collect the required data [37][38].

- Step 2 (processing algorithm): The major AI algorithms are classified into supervised learning (i.e., the model is established based on the training dataset in which the label of each instance is known), unsupervised learning (i.e., the label of each instance in the training dataset is unknown), and reinforcement learning (e.g., the agent continuously interacts with the environment to learn how to correctly take actions). According to the required goals and objectives, AI algorithms are chosen to solve the problem or provide actions [39][40][41][42].

- Step 3 (Decision output): Through the processing algorithms, the output decision provides a judgment, choice, or action [43][44][45].

- Knowledge database: The knowledge database provides the AI system with the stored experience and decision data to assist the operation.

Recent AI technologies and applications that have received much attention include machine learning and deep learning for data analysis (e.g., supporting and amplifying human cognitive functions for physicians delivering care [46], and helping users to focus their attention to find visual elements more efficiently [47]), prediction (e.g., predicting the compressive strength of geopolymer concrete [48], detecting COVID-19 [49], and predicting future energy use based on historical data [50]), object classification (e.g., automatic image analysis using a variety of AI techniques [51], and indoor obstacle classification with a good balance between classification accuracy and memory usage [52]), natural language processing (e.g., extract information in health records using AI natural language processing techniques [53], and effectively use sophisticated natural language processing technology on large volumes of legal texts [54]), recommendation (e.g., assessment of agriculture land suitability using an expert system by integrating sensor networks with AI systems [55], and an AI recommendation service [56]), intelligent data extraction (e.g., ensuring high-confidence NIR analysis in the AI performance of the IoT [57], and building a AI-based cloud database that can support user demand [58]), and reliable communications (e.g., mitigating and combating IoT cyberattacks using AI [59], dynamically scheduling flexible transmission time intervals using machine learning [60], and reliable IoT system for data transmission [61]).

3.2. AI Applications in SGs for Smart Manufacturing

Based on the framework of SG technologies (**Table 1**), most SG systems aim to achieve smart power control and demand-side management, in which the AI applications of SGs include prediction stability, power load management, power supply management, and prediction, and these AI applications consist of four modules (**Figure 2**). Recent surveys in [62][63][64] have introduced how AI can assist in optimizing the SG systems. This survey focuses on applying AI to optimize the SG systems to achieve the goals of smart and sustainable manufacturing. Recent AI applications in SGs include operating cost reduction [65], power system management and load control [66][67], demand-side management [68][69], and power detection [70][71]. For demand-side management in SGs, Khan et al. [72] used nature-inspired-based AI techniques to address real-time scheduling for the coordination of appliances while minimizing the load curve gap and cost. To minimize utility company costs, Ma et al. [73] established a cost optimization model and then derived the optimal relay assignment as well as power allocation. To establish an accurate system prediction model, Babayomi et al. [6] defined a sequence for predictive controllers to seek optimal control.

4. Optimization Applications for SGs in Smart Manufacturing

This section introduces the optimizations for SGs in smart manufacturing, including smart manufacturing environment and technology importing, and the applications of optimizing SG systems for smart manufacturing.

4.1. Smart Manufacturing Environment and Technology Importing

Smart manufacturing is characterized by the use of highly automated production equipment, which is connected and communicated through the IoT. It is beneficial for data collection and big data analysis [6] and further AI learning (including machine learning and deep learning) to predict possible production conditions (e.g., using decision trees to predict categorical values, and using the self-organizing map to predict the physical quality of products manufacturing) and judge production operations (e.g., using additive models to correct short-term forecast errors during judgment) [74] to provide advanced manufacturing operations of self-perception, automatic decision-making, and automatic execution. Although different countries have emphasized different smart manufacturing technologies and applications, most of them have focused on cyber-physical systems, big data analysis, cloud computing, and energy saving [75][76]. With advances in smart manufacturing technologies, highly automated equipment has been introduced, such as human–machine systems, robots, automated guided vehicles, and automated storage and retrieval systems [77][78][79]. Although smart manufacturing has made manufacturing processes more effective and efficient, these advanced processes through highly automated human–machine systems and high energy-consuming equipment consume increasing energy and cause increasing environmental issues [80].

The SG is a key to the supply and management of energy in smart manufacturing [81]. As illustrated in **Figure 3**, a smart manufacturing framework based on the SG system [4][82][83][84][85] consists of the following components:

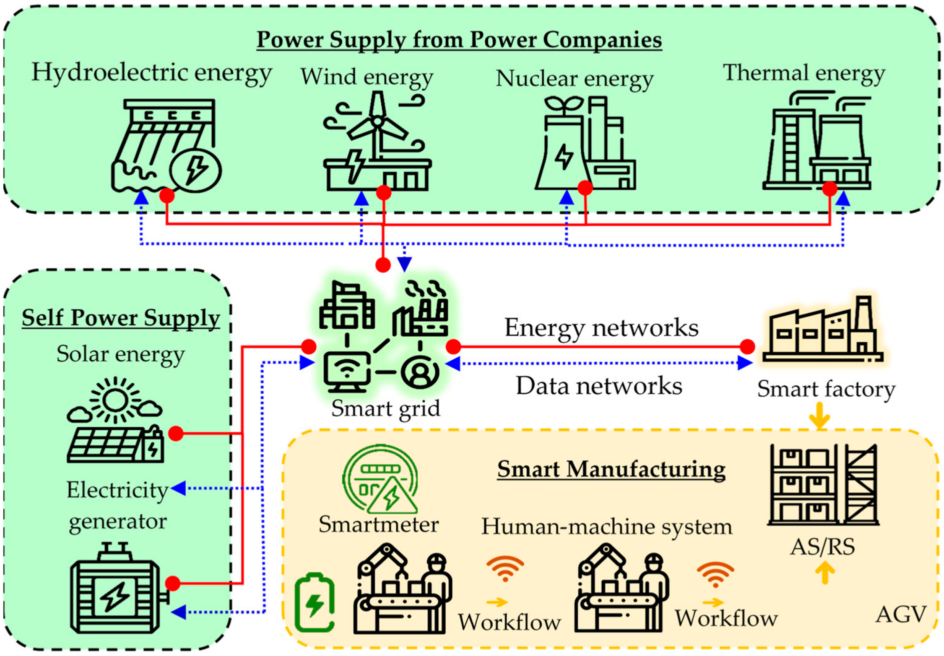

Figure 3. Illustration of a smart manufacturing framework based on the SG system [4][82][83][84][85].

- Smart manufacturing: The smart manufacturing environment includes human–machine systems, automated guided vehicles (AGVs), automated storage/retrieval systems (AS/RS), and other equipment, which are monitored by smart meters.

- Power supply from power companies: The energy required for manufacturing processes is supplied by hydroelectric energy, wind energy, nuclear energy, and thermal power from the power companies in the SG.

- Self-power supply: A lot of smart factories set up solar panels and energy generators on the SG to control the power supply independently.

4.2. Optimizing SG Systems for Smart Manufacturing

To optimize their SG systems to avoid shutdowns in continuous manufacturing operations, as shown in **Table 2**, the applications of using AI and optimization technologies for SGs in smart manufacturing are detailed as follows:

Table 2. Related AI and SG technology application works in manufacturing.

Optimization Application	Technology and Implementation	Reference	Note
Energy cost management	**Machine learning, deep learning, algorithm, linear programming**	[86][87][88][89]	**To effectively reduce the cost of energy use in smart manufacturing, AI technology is introduced into the SG for optimizing load control and power scheduling.**
Implementation of smart meters	**Algorithm, grid-edge technologies, smart meter**	[90][91]	**Smart meters are implemented in the SG, and the measured data is analyzed by AI algorithms and models to manage power consumption more accurately.**
Reliable energy system	**Machine learning, deep learning, deep neural network**	[92][93]	**AI technologies are used to evaluate the reliability of SGs and simulate possible attacks on IoT-based energy networks to ensure a reliable energy system.**
Establishment of the digital twin	**Digital twin technology, algorithm**	[94][95][96]	**The digital twin was established to provide an effective configuration and solution for the energy consumption of complex smart manufacturing systems.**
Big data-driven optimization	**Machine and deep learning, sensor**	[97][98][99]	**Big data from manufacturing is collected and analyzed by deep learning to control energy consumption and achieve sustainable development of the manufacturing process.**
QoS of communication networks and data collected	**Controller, sensor**	[100][101][102]	**To ensure QoS communication quality in the complex smart manufacturing framework based on the SG, sensors and controllers are used for data collection to improve energy utilization and energy saving.**

- Energy cost management: Khalid and Powell [86] developed an algorithm for forecasting manufacturing energy load to effectively reduce peak facility power. Lu and Hong [87] proposed an incentive-based demand response algorithm to enable the SG system to have reinforcement learning and deep neural network capabilities. Targeting natural gas demand in the SG, Dababneh and Li [88] proposed a modified simulated annealing algorithm to establish a production scheduling model to allow manufacturers to reduce energy costs. Wu et al. [89] proposed a mixed integer linear programming model to schedule actual multi-tasks to minimize the energy cost.

- Installation of smart meters: To effectively manage energy consumption, Zakariazadeh [90] adopted smart meters and an artificial bee colony-based random forest clustering algorithm for data classification and analysis, and the adopted method was more accurate than other classification methods. Venkatraman et al. [91] developed a smart meter data-driven rate model to recover distribution network-related charges and imported grid-edge technologies to meet the needs of consumers of different power scales and save costs.

- Reliable energy system: Behara and Saha [92] carried out a reliability assessment for SG-integrated distributed power-generating with AI methodology-based search algorithms to ensure the reliability and accuracy of the power system. Rouzbahani et al. [93] simulated the SG system being attacked by the IoT energy network through an attack generator algorithm and used the deep neural network to detect it to establish a safe and reliable energy system.

- Establishment of the digital twin: Wang et al. [94] surveyed the approaches and applications of digital twins for energy systems. Jiang et al. [95] proposed a complex SG system with the digital twin based on data and knowledge for duplication of similar unit-level and management. In view of the large energy consumption and fluctuations in the manufacturing system, Mourtzis et al. [96] developed the stored energy allocation model based on the digital twin technology to optimize energy allocation and reduce CO_2 emissions.

- Data-driven optimization: Mourtzis et al. [97] surveyed smart manufacturing energy policies and cases, in which a lot of actual cases used SG data collection and analysis and machine learning methods to control energy consumption and electricity prices, allowing continuous data-driven optimization. To monitor and optimize the energy consumption of manufacturing factories, Bermeo-Ayerbea et al. [98] proposed a data-driven energy prediction model to control machine energy consumption and fault warning and improve energy efficiency. Meng et al. [99] summarized the solutions to energy consumption in the manufacturing industry and explained how to make smart manufacturing move forward toward sustainable development through big data collection and the development of decision-making technologies.

- Quality-of-service (QoS) of communication networks and data collected: Faheem and Gungor [100] considered that electromagnetic interference and multipath effects exist at the manufacturing site due to the use of industrial wireless sensors and IoT, and they would affect the QoS for data collection. They then proposed a QoS-aware data acquisition protocol model to reduce data error rate and improve the quality of manufacturing data communication. Qureshi et al. [101] proposed a software-defined network (SDN) for the energy internet to improve the response time and QoS of the controller, which can also increase the utilization rate of green energy in the SG system. In the complex SG framework, Faheem and Gungor [102] applied dynamic clustering-based energy efficiency and a QoS-aware routing protocol to improve the quality of information transmission.

In addition, to collect data for data analysis and machine learning, the IoT infrastructure (e.g., smart meters, sensors, and controllers) is installed in smart factories. Still, it leads to potential cybersecurity issues, which should be addressed by various methods for cybersecurity and information protection [103][104].

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