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Shaping future low-carbon energy and transportation systems: Digital technologies and applications

Jie Song[1,2], Guannan He[1,2] ✉, Jianxiao Wang[2] and Pingwen Zhang[3]

ABSTRACT

Digitalization and decarbonization are projected to be two major trends in the coming decades. As the already widespread process of digitalization continues to progress, especially in energy and transportation systems, massive data will be produced, and how these data could support and promote decarbonization has become a pressing concern. This paper presents a comprehensive review of digital technologies and their potential applications in low-carbon energy and transportation systems from the perspectives of infrastructure, common mechanisms and algorithms, and system-level impacts, as well as the application of digital technologies to coupled energy and transportation systems with electric vehicles. This paper also identifies corresponding challenges and future research directions, such as in the field of blockchain, digital twin, vehicle-to-grid, low-carbon computing, and data security and privacy, especially in the context of integrated energy and transportation systems.

KEYWORDS

Digitalization, decarbonization, energy system, transportation system, energy and transportation integration.

Energy and transportation are the two sectors with the largest carbon emissions in China and worldwide[1]. Under the strategic goal of achieving "carbon peaking and neutralization", the low-carbon transformation of energy and transportation systems is inevitable for China[2].

Digital technologies are transforming our lives, including the energy and transportation sectors. Digitalization is a key trend that provides options for energy demand and carbon emissions reductions[3,4], although doubts have been casted on whether the local energy savings from networked digital devices could compensate for the increasing energy use of the devices[5]. Digital technologies can also help shape next-generation transportation systems towards intelligent and sustainable design[6,7].

Importantly, how digitalization could facilitate timely and cost-effective decarbonization has attracted interest from both academia and industry. Digitization entails sensing, transmission and computation, i.e., data generation, data transmission, data storage and transformation, and data application (data value generation). From the perspective of data value stream, the generation of high-quality data relies heavily on the advancement of infrastructure, including energy and transportation sensors. Meanwhile, the development of 5G and 6G technologies aids in the speedy transmission of data to fulfill the demands of the big data era for the timeliness of massive amounts of data. With the support of more sophisticated mechanisms and algorithms, data can create values in various application scenarios, and digitalization can help the industry prosper.

Here, we review the digital technologies and applications that help shape the energy and transportation systems towards low-carbon economies, from the perspective of infrastructure, mechanisms, and algorithms. We start by reviewing the digital infrastructures needed for energy and transportation applications, including sensors, communications, and computing devices. Then, we review the common mechanisms and algorithms enabling the use and value generation of digital technologies in energy and transportation applications, including Internet of Things (IoT), cloud computing, blockchain, data trading, and digital twin. We also review the system impacts of digitalization, including how digital technologies would shape energy and transportation systems, their carbon footprints and synergies through electric vehicles (EVs). Finally, we discuss the remaining challenges of applying digital technologies in low-carbon energy and transportation systems and suggest future research directions.

1 Infrastructure

In this section, we review the infrastructures that provide the foundation for the application of digital technologies, namely sensors, communications, and computing devices, and discuss how computing links various types of infrastructure to enable digitalization.

1.1 Sensors

Sensors are extensively installed in (almost) every physical device in IoT network systems like global positioning system (GPS) and infinite sensor network (ISN)[8]. Sensors are (inter)connected via the Internet or wirelessly, allowing sensor elements to communicate with individuals, and to monitor equipment[9] through remote control. Sensors are widely used in energy and transportation systems.

Energy applications

Numerous sensors have been installed on the load side to facilitate the intelligence of the energy system. For example, in the field of

[1]Department of Industrial Engineering and Management, College of Engineering, Peking University, Beijing 100871, China; [2]National Engineering Laboratory for Big Data Analysis and Applications, Peking University, Beijing 100871, China; [3]School of Mathematical Sciences, Peking University, Beijing 100871, China
Address correspondence to Guannan He, gnhe@pku.edu.cn

smart homes, Kodali proposed a sensor-based wireless home security system that allows for the remote management of home appliances[10], a system that is low-cost, low-power, and based on GSMC/GPRS (global system for mobile communications/general packet radio service)[11]. In terms of sensor installation, the wireless home network consists of three basic sensor nodes: fire alarm nodes, infrared identification nodes, and entry door security nodes.

Additionally, sensors are employed in monitoring technologies. Information such as parameters related to operating conditions (e.g., voltage, current) as well as the damage and aging of the battery (e.g., leakage current, power loss factor) can be tracked using condition monitoring. Low-power wireless sensor networks can provide condition monitoring for more efficient management, while many other sensors are installed on high-voltage terminals (e.g., busbars, circuit breakers)[12].

For instance, the safety of the natural gas transmission infrastructure is crucial to a smart and integrated energy system. And to improve the safety of the natural gas infrastructure, Iwaszenko et al. have developed an unmanned aircraft equipped with a remote methane detector to inspect natural gas pipelines for leaks[13].

Transportation applications

Sensor-based intelligent transportation systems (ITSs) are expected to improve traffic safety and efficiency. Sensing platforms are broadly divided into two categories in transportation systems: (1) in-vehicle sensing platforms that collect data on vehicle conditions[14]; (2) sensing platforms that collect data on traffic conditions, which are generally installed around urban roads[15].

Sensors in vehicles generally include pressure sensors, which check tire pressure with sound, light, or vibration and warn the driver when it is low[16], and distance sensors, such as radar systems, which keep an eye on the surroundings of the vehicle to spot obstacles, children, pets, and other vehicles in order to avoid dangerous situations[14].

Collecting traffic data using roadside sensing devices has become an indispensable part of ITSs. Real-time road traffic data are first gathered by road sensors, and further processed and analyzed to regulate and improve traffic conditions. Depending on where they are installed, in-road sensors could be categorized into two types: intrusive and non-intrusive[15]. Intrusive sensors are placed on road surfaces. For instance, Rajab et al. introduced a multi-element sensor, which can classify vehicles accurately according to their tire distance, tire count, and vehicle speed[17]. Non-intrusive sensors are deployed around the road to detect moving cars. For example, Quang and Thang introduced an infrared sensor that is positioned on the roadside to measure the speed of the vehicle with few mistakes[18]. Furthermore, radio frequency identification is often used for vehicle recognition in parking lots, gated communities, and toll road access control[19].

Sensors in energy and transportation

Nowadays, sensors are extensively employed in the field of EVs. Their application focuses on the integration of sensors into the electric drive system, and the sensors primarily used in the electric vehicle industry include speed/position sensors, voltage sensors, current sensors, etc[20]. For example, lithium-ion batteries are fitted with a battery management system (BMS) to keep track of their performance and the energy storage status of the electric vehicle, and the operation of the BMS relies heavily on the sensors installed inside the battery[21].

1.2 Communications

Importantly, 5G, the "fifth generation" cellular communication network, can provide high-performance communication services with high capacity and low latency[22]. 5G is widely used in autonomous driving, virtual reality, and the IoT. 5G technology has developed rapidly in China, which has laid a solid foundation for the development of 6G. The biggest advantage of 6G over 5G lies in the diversification brought by its global ubiquitous coverage, that is, the diversification of data sources, applications, communication means, and computing. The 6G network would have larger information capacity, higher transmission rate, lower transmission delay, larger number of connections, higher spectral efficiency, and higher energy efficiency, thus supporting a wider range of applications.

Energy applications

5G/6G is a type of infrastructure that can connect upwards of billions of objects to each other and transmit huge amounts of data at extremely fast speeds. While 5G/6G enables extremely fast data transmission and global ubiquitous coverage, the energy consumption required by 5G/6G base stations is also increasing. As such, how to reduce the operating cost of 5G/6G base stations, save energy consumption, and reduce emissions has become a research hotspot[23].

5G/6G infrastructure has great potential for providing demand response service to the grid. Liu et al. analyzed the advantages and disadvantages of utilizing 5G base stations in demand response, and simulated its economic feasibility[24]. Hui et al. mentioned that 5G technology has many applications in smart grid due to its advantages of fast transmission speed and high reliability[25], and its demand response could become more efficient as a result of these advantages.

As has been mentioned in the previous subsection, drones can be applied to survey energy sources. Unmanned aerial vehicles (UAVs) can also be used in environmental monitoring, emergency communication, transportation control, remote sensing and many other application scenarios[26]. As the requirement for remote control of UAVs grows, networked UAVs need to install more robust communication systems. 5G and upcoming 6G also play a vital role in drones[27]. 5G/6G offers higher speeds, lower latency, and a wider frequency range than 4G, allowing more devices to be supported while reducing interference from other channels[28]. This enables remote operators to easily monitor and control drones in real time, without having to be present at a specific control center.

Transportation applications

5G-based ITSs could greatly enhance driving safety. Roy and Misra established a plan for its application in road traffic, which can help quickly switch between different service providers to ensure driving safety and help users make decisions[29]. The data transmission network environment will be more complex in future edge-computing based ITSs. Saraiva et al. invented an application-driven vehicle network framework based on 5G to adapt to heterogeneous demands between the number and moving speed of vehicles[30]. Because the moving speed of vehicular ad-hoc networks is extremely fast, the link and bandwidth between ITSs and software-defined network (SDN) are prone to problems, so Din et al. proposed to enhance the capability of ITSs through a new SDN architecture on the basis of 5G[31]. Tan et al. proposed a 5G-based space-air-ground integrated network (SAGIN) solution with traffic efficiency enhanced by speech emotion recognition[32], which enables better interaction between humans and vehicles.

5G technology is mainly used in automotive networks and cloud computing in the field of autonomous driving. Ibrahim et al. conducted intensive research on 5G wireless antennas using 26 GHz to 28 GHz, which aims to install a mock-up of a wireless device in a car to enable 5G communications[33]. Shah et al. noted that an important feature of 5G is proximity services (ProSe), which can directly connect data to the system in autonomous driving and requires no data search in or data transmission with the data center[34]. Pattinson and Chen studied the data transmission and information security transmission of high-precision maps to improve the safety of autonomous driving and to provide solutions for the testing of autonomous driving[35].

5G/6G in energy and transportation

5G/6G technologies are also being used in the EV sector at present. Intelligent and interconnected EVs become the major trend[36]. For smart electric vehicles, the more effectively they apply the technology of smart energy management, the more competitive their products are. With more advanced network technologies, 5G/6G guarantees the stable transmission of information in intelligent transportation, while an integrated system established for smart vehicles allows for better monitoring of the level of smart energy management in electric vehicles.

The delivery of electric vehicles can be less delayed by virtue of 5G's low latency. Tanwar et al. proposed a scheme with a double auction mechanism over 5G networks to optimize the revenue problem between EVs and charging stations, which ensures low latency and high stability of data transactions in between[37]. By installing frequency meters in or near charging stations for each load zone, and using a novel 5G network architecture to implement frequency regulation services for plug-in electric vehicles (PEV), a new system framework is built to solve the problem of coupling FM-based services and smart charging for electric vehicles. This enables applications with very low latency to operate efficiently[38].

1.3 Computing devices

Embedded system

An embedded system is a small-size computer system based on microprocessor with dedicated functions, including monitoring, data acquisition, analysis, and control, within a larger system.

In the energy sector, embedded systems are widely applied in applications such as renewable energy management[39,40], battery management[41], smart metering in energy consumption[42–44], and carbon emission monitoring[45,46]. In the transportation sector, embedded systems could help vehicles and drivers become more connected[47–49] with dedicated smart vehicle systems[50], forming the Internet of Vehicles (IoV)[48,49] or social IoV[51–53].

Server/data center

Data centers represent the information backbone of an increasing digital world and are a critical type of infrastructure for supporting future digital energy and transportation systems[54–56]. Some research has focused on developing low/zero-carbon data centers, which requires integrating renewable energy while ensuring high availability[57].

Relevant standards for low-carbon data centers have been formulated to encourage more usage of renewable energy like hydropower, wind power, and solar energy[58–60]. To help reduce the internal energy consumption, measures such as load reduction[61,55], cooling system management[62–64], and enhancement of waste heat recovery[65,66] can be taken for data centers.

2 Common mechanisms and algorithms

In this section, we review the common mechanisms used to enable the application of digital technology in energy and transportation systems and discuss related algorithms.

2.1 IoT

IoT refers to collecting information such as the status and shape of objects, environments, or people through various sensing and identification technologies, and transmitting the information through a network, potentially with fast connection between things and people anytime, anywhere, to make management more efficient[67].

The IoT is widely used, such as smart homes, transportation, agriculture, healthcare, industry, entertainment, and surveillance[68].

Energy applications

The applications of IoT in energy systems can be divided into the field of sensors and communication.

IoT-based signal processing is widely applied in wireless sensor networks for assisted living and information filtering. Buildings consume 60 percent of the world's electricity, and building management systems can use wireless sensors to collect a wealth of building data as a way to monitor and regulate energy use and reduce costs[69].

Communication based on multiple-input-multiple-output (MIMO) has been widely applied in the IoT field. For example, Baniata et al. proposed an energy-efficient unequal hybrid clustering routing protocol based on MIMO to help improve energy efficiency[70]. Elhebeary et al. proposed a low power consumption and no energy harvesting system for the IoT[71], with a dual-mode DC-DC converter that not only harvests energy from microscale photovoltaic sensors but also supplies supercapacitors with energy that can be stored in boost mode.

Using an integrated energy supply network, an energy management platform based on IoT could be built to deploy demand response energy management for industrial purposes[72]. With IoT technology, Wan et al. developed an energy monitoring system for buildings[73]. The system used smart meters with RS485 interface to collect data on building energy consumption, which was then transmitted via TCP/IP protocol to energy regulation service providers for processing and analysis[73]. Rafsanjani et al. proposed an innovative smartphone energy assistant framework based on IoT technology to track each occupant's energy use and offer personalized services to optimize resident usage[74].

Transportation applications

The intelligent traffic system (ITS), also known as the Intelligent Transportation System, integrates information, data communications, sensors, and computer technology in the areas of transportation, service control and vehicle manufacturing. The IoT can assist in creating a robust platform for ITSs' perception and identification of traffic elements.

One important area in intelligent transportation is navigation or route optimization. Yang et al. made full use of the user's mobile device to collect data[75], and Dweik et al. placed side units at designated positions on the road for traffic condition prediction and best route calculation[76], thereby reducing the journey time, exhaust emissions, and energy consumption of the car.

The application of the IoT in parking mainly involves detecting parking spaces in parking lots and informing the owner of parking space information or transmitting the information to a centralized system. IoT-based frameworks were introduced for intelligent parking space management with consumer-cloud coordination[77,78].

Traffic accidents can be alerted in advance via IoT. It has been suggested that IoT could be used to monitor the driver's awareness[79] and road conditions[80] for preventing possible accidents. Celesti et al. built a cloud platform to visualize traffic, which can predict or even avoid traffic accidents through vehicle speed and position data[81]. Bansal et al. proposed a system based on machine learning and IoT that can probe road surface leveling. This system can help detect road conditions and improve driving safety[82].

IoT in energy and transportation systems

As a result of technological advancements, IoT is widely used in the manufacturing of EVs. An intelligent framework based on IoT and edge computing has been proposed for the efficient operation of V2G. This framework can effectively provide active power regulation[83], load matching, current harmonic filtering[84], etc. It can also manage decentralized energy sources, increasing the grid's stability and reliability as well as its power efficiency[85].

Geographic migration for smart cities using fogged vehicles for processing was proposed by Liao et al[86]. Using a vertebrate topology, a scalable IoT data center offers enhanced fog computing. Smart IoT applications that are hosted in the cloud link individual nodes to provide data monitoring and analytics services, as well as ensuring network security through infrastructure monitoring[87].

Algorithms of IoT

Many algorithms are applied to IoT as it develops. Yan et al. based on neural network (NN)-assisted power control algorithms, reduced the time required to compute MIMO encoding and decoding by a factor of 30[88]. For ITS applications dedicated to traffic management and traveler/passenger information, real-time prediction of future traffic conditions is a major challenge. To make traffic predictions faster and more accurate, Fusco et al. applied Bayesian networks of different sizes and artificial neural networks for road connection speed prediction[89]. Liu et al. suggested a simplified coupled hidden Markov model for motion intent inference in autonomous driving[90]. To handle the challenging problem of finding parking spaces in large cities, Wu et al. used a Markov random field (MRF) framework to fuse the outputs of SVM classifiers[91]. Hou et al. used a random forest model to predict traffic flow, making the prediction results more accurate[92]. In response to the frequent traffic issues, IoT-based safe driving systems have been developed to improve safety. Some scholars have used clustering to locate road anomalies and accident-prone areas in times of congestion outbreak, relief and severe congestion, and the technique they proposed outperforms the nearest neighbor approach in traffic prediction[93,94].

2.2 Cloud computing

Cloud computing, an Internet-based computing model for delivering information technology services, can provide information and resources of shared software and hardware for computers services and other equipment as needed[95]. Additionally, through migration of virtual machine technology, workloads can be transferred among geographically dispersed data centers so that renewable energy available elsewhere could be made use of[96].

Energy applications

The management and optimization of energy systems have seen a rise in popularity of cloud computing. For example, the energy cloud can be seen as a platform with economic and technical requirements for fusing distributed renewable energy systems with intelligent technologies (such as micro grid, smart instruments, storage facilities and IoT)[97]. To better manage the energy system using cloud computing, Schaefer et al. formulated the fundamental requirements for an energy cloud and its management, and discussed the major challenges as well as opportunities as the technology evolves[98]. Using fog computing to relieve the burden of data analysis, processing, and storage, Kaleemullah proposed an efficient energy management system based on the cloud[99]. Petri investigated the energy management of HVAC (heating, ventilation, and air conditioning) systems in architectures supported by IoT and edge/cloud technologies[100]. Relying on reliable data on the use of the edge computing mode, Agostinel et al. evaluated the effectiveness and efficiency of a smart automation and optimization system for energy conservation of residential quarters in raising the self-generated energy threshold and meeting the demand for a nearly zero-energy building[101].

Transportation applications

Advances in the IoT and cloud computing are opening up possibilities for better traffic control and customer-oriented services[102]. Cloud computing can store and process collected information (e.g., from activity lights, stopping meters, cameras, city sensors, etc.), and take a verifiable register of road design behavior, allowing street offices to make informed decisions on traffic and infrastructure management including when to modify or repair roads and traffic lights to boost the efficacy of ITSs[103]. Pop et al. proposed a route planning strategy that integrates the concept and implementation support of cloud computing for multi-modal ITSs[104]. Latency and bandwidth limitations can be resolved by cloud computing deployed close to vehicles and ITSs sensors[105]. Dai et al. developed a joint edge computing with caching scheme for vehicle networks that dynamically arranges edge computing and caching assets to maximize framework utility[106]. Using deep reinforcement learning, they also produced a new resource management scheme[106].

Recent years have seen the emergence of the concept of the "Vehicle Cloud". The "Vehicle Cloud" offers three major types of services. The first one, Network as a Service (NaaS), supports a permanent internet connection and provides paid network services for other vehicles without internet access. The second one, known as Storage as a Service (SaaS), shares on-board storage with other vehicles in need of additional storage. The third type of service is Data as a Service (DaaS), in which users of intelligent vehicles can request specific services such as video playing, city map assistance, and notification of road conditions[107].

Cloud computing in energy and transportation systems

Future automotive applications are actively embracing the coexistence of cloud and edge computing[108]. To accelerate computing and communication, Jiang et al. proposed a framework applying edge computing, which enables heterogeneous connecting for EV networks in an energy-efficient way[109].

Vehicular cloud computing (VCC) is another approach to apply cloud computing to in-vehicle networks[110]. Zheng et al. proposed a computational resource allocation scheme that maximizes the overall long-term benefits of VCC systems[111]. Electric vehicle cloud and edge (EVCE) computing offers seamless connectivity in heterogeneous automotive environments, aggregating dispersed EVs into a common pool of resources and invoking EVs for local, flexible use[112].

Algorithms of cloud computing

Machine learning algorithms have been widely studied for cloud computing applications. Liu et al. proposed a cloud-based quantum chaotic neural network algorithm model (C-QCNNA) to solve various intractable multi-objective low-carbon supply chain problems[113]. In this article, multilayer quantum neural networks provide supervised training in place of a backpropagation algorithm. Numerous algorithms, such as reinforcement learning algorithm based on power spectral density (PSD)[114] and heuristic algorithm for green energy fog network[115], have been applied to balance workload delay and energy consumption. Abbasi et al. introduced an energy-efficient method with learning-based classifier system for workload distribution to address the energy consumption and cost optimization of cloud computing in ITSs[116].

2.3 Blockchain

In both academia and industry, blockchain is the ideal tool for bringing innovative changes to a decentralized power system and easing the transition towards a smarter grid[117]. A blockchain is a distributed database or ledger in which information transactions are first verified by consensus algorithms, and then recorded into a block as a basic unit[118]. An ever-expanding chain will be formed as a block is created and appended to the blockchain with reference to the previous one. Blockchain could provide immutable cryptography and distributed consensus to ensure the security and decentralization of information flow. More importantly, it allows the smart contracts to be automatically executed in a distributed network[119]. Instead of managing all transactions through a third party, the blockchain is self-governing where each community member has a copy of all records, and a consensus should be achieved before any block is created. Consensus algorithms research is an active field, and different consensus algorithms with different levels of scalability and security are adopted in various applications.

Early research initiatives and pioneer programs have shown that blockchain technology may offer solutions to problems faced by the energy industry[120]. A survey conducted by the German Energy Agency shows that about 20% of the participants, including utility companies, generation companies, energy suppliers, aggregators, and network operators, believe that blockchain will change the way of energy supply in future. Furthermore, over 50% of them are planning to or have already taken initiatives to develop blockchain technology[121].

Energy applications

Blockchain is primarily used in the energy sector as a P2P energy trading platform. Brooklyn MicroGrid is the first P2P energy trading system based on blockchain that has completed a three-month trial in a local community[122]. During the trial, prosumers could conduct electricity transactions with their neighbors under Ethereum-based smart contracts without a third party.

Aitzhan and Svetinovic applied blockchain in a distributed energy trading system using multi-signature technology and anonymous information flow, and they proposed a solution to ensure network security during trade without a third party[123]. Burger et al. analyzed an energy trading application based on blockchain technology and predicted its prospect. They contended that Enercoin should take the role of the Euro in energy trading[121]. Although forward-looking trials like MicroGrid have been conducted and conclusions on applicability have been drawn, these studies could not be widely used in practical applications since energy trading cannot currently be done without supervision. To bridge the gap between blockchain technology and real practices in energy trading, Mannaro et al. presented a weak centralization method[124] that employed blockchain to record power transactions and handle settlement automatically amongst users. The weak central institution is intended to serve as a special node that oversees the blockchain. P2P energy trading in a decentralized market can create incentives for prosumers and promote distributed generation investment, offering more opportunities for smart grid transition[122].

Transportation applications

Before blockchain technology is widely adopted in transportation systems, the system security needs to be proved. Sharma and Park applied blockchain to ITSs design and suggested a secure distributed network to enhance the security and privacy[125]. Xu et al. designed a blockchain-based negotiation protocol for the multi-TA (trusted authority) network model that could shift the computational loads of TAs to roadside units in order to boosft authentication efficiency. In addition, multiple TAs could employ blockchain technology to manage vehicle-related information, making it easy to authenticate the identities of automobiles amongst TAs[126].

Additionally, blockchain technology may also be used in services such as vehicle management and traffic control. Buzachis presented a multi-agent system based on bidirectional communication between vehicles and infrastructure which can manage vehicles safely through interconnection using edge-of-things (EoT) and blockchain[127]. Zia proposed a blockchain-based distributed transportation network, B-DRIVE, for smart city management, which could connect a large number of IoT devices in vehicles or on roadside infrastructure to a data center[128]. The network could link devices located across the city to different nodes, and record transportation data on a blockchain with a time stamp[128].

Blockchain in energy and transportation systems

Future energy systems, such as EVs[129], require more flexible demand-side energy resources like demand response (DR) programs[130] to balance the changes in the supply and demand of renewable energy. Flexible resources have a limited capacity, and are spread out across a vast region, so it is difficult to integrate them into centralized management and control. Due to its inherent decentralized structure, blockchain technology is critical to the integration of flexible resources[131]. It could offer smart contracts to enable the transparent involvement of DR resources by specifying their roles and incentives, and providing participants in DR programs with full access to energy transaction data. In addition, blockchain technology could provide necessary information to assist in grid management and control in applications like V2G[132] and microgrids[133].

Algorithms of blockchain

Intrinsically, blockchain relies on various consensus algorithms applied in computer science to unify disparate processes or systems around a single data value. After the consensus has been reached, the data appended to the chain will be verified and distributed throughout the whole network, thus being accepted and protected. Common consensus algorithms include proof of work (PoW), which is used in bitcoin community, proof of stake (PoS), which is used in Ethereum, proof of concept (PoC),[134,135] and proof of authority (PoA), etc. PoW[136] and PoS[125,137], two of the most used consensus algorithms, are widely adopted in blockchain applications in energy and transportation sectors. Using a blockchain based on PoW consensus, Thakur et al. developed a P2P energy trading platform locally without trusted third parties[136]. Kang et al. also embraced the idea of P2P energy trading, but their research was based on PoS consensus algorithm, with the aim of enabling local trading of electricity among EVs in smart grids to relieve the peak load of network and offer stability[137]. Sharma et al. coupled IoT with blockchain in an ITS to guarantee the security and privacy of the whole transportation network based on Ethereum[125]. As the first consensus algorithm used in the bitcoin, PoW reaches consensus according to the work of miners, a method reliable and safe, yet resource-consuming and not so scalable[138]. PoS consensus algorithm, by contrasts, uses the stake of validators instead of the efforts miners offered to ensure the data transactions, which is a more scalable and faster approach[138].

2.4 Data trading

Data is the new oil. The amount of data we collect worldwide is exploding because of the emerging digital technologies and applications that permeate our daily life[139,140], especially the intelligent systems based on the Internet of Things. Furthermore, a massive amount of data is required among data-driven firms[141]. The efficient utilization of data calls for data trading[142]. Figure 1 shows how data trading could produce values in low-carbon and transportation systems. Useful data about energy consumption, renewable energy generation, traffic congestion, transportation schedules, and so on are collected by sensors and systems. Data owners can decide how much data they trade and with whom. Data have different properties from general commodities, such as replicability and non exclusivity. Therefore, the key challenges include rights confirmation, pricing, security, and privacy protection[141,143,144].

Energy applications

The main application of data trading in energy systems is uncertainty reduction. The uncertainty in renewable energy power generation[145] and power loads[146] can make them challenging to be predicted accurately, bringing risks to utilities. Uncertainty reduction is useful for power systems such as energy hub scheduling[147], demand response aggregators[148], robust decision-making[149], and the operation of microgrids[150]. With data trading, the micro or private data can be fully and effectively used, and variations in random factors can be better forecast, which could aid decision-making in uncertain environments to improve energy efficiency and bring economic benefits.

Transportation applications

Data trading in vehicular networks, which is still in the bud[151], can offer new chances in remote information processing of vehicles to enhance our life quality. The proper vehicular data sharing can aid in the improvement of active security measures, virtual assisted navigation services, remote service reservation, and live updates on driving conditions with engineering costs reduction. It was recommended to switch from free data sharing to data trading in vehicular networks to encourage more vehicles to participate in data trading[152].

Data trading in energy and transportation systems

Through data trading, energy data can be integrated with other types of data for more applications. For example, Wei et al. discussed data integration with transportation systems, since EV driving and charging affect both the transportation system and the energy system[153]. By combining charging data with traffic flow and pressure data, the traffic flow can be better predicted and the public service for EVs can be enhanced. Data trading among EVs could enable more effective management of energy demand-supply[154] and EVs have access to service suppliers for information about charging schedules. Additionally, surplus energy could be traded among EVs efficiently with the assistance of social communication[155].

Algorithms of data trading

Data trading includes both raw data and data products. The data application service development platform can provide data products and data services after depth analysis based on algorithms such as deep learning, statistical, and graph analysis algorithms[156]. In addition, data of different scales can be integrated within the computing framework of parallel, stream, and hybrid computing. Then, the integrated data can be applied in various scenarios with algorithms such as data mining and machine learning.

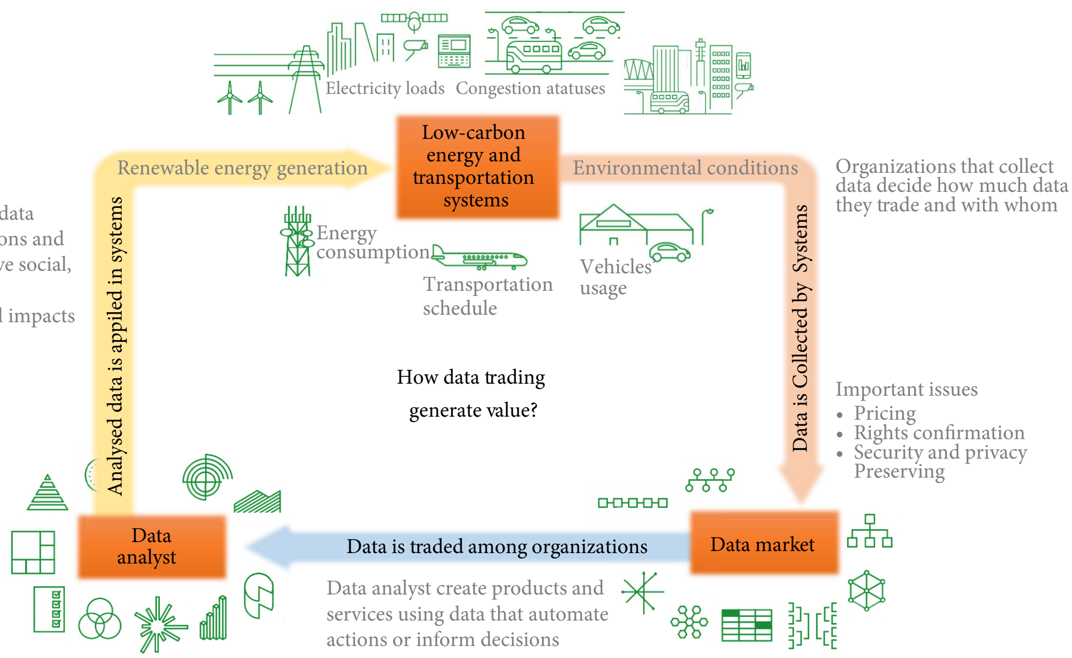

Fig. 1 **How data trading could produce values in low-carbon and transportation systems.**

There are also many key technical issues in the process of data trading, which include pricing, rights confirmation, security, and privacy protection.

As for data pricing, Guo et al. indicated that it can be divided into two steps: evaluation and pricing[156]. Evaluation can also be divided into two steps: firstly, analyzing how much data contribute to the uncertainty reduction; and secondly, analyzing how much the reduction of uncertainty contributes to the economic interests of stakeholders. Uncertainty expressions include interval number[157], fuzzy number[158], random variable[159], and uncertainty set[160], whose corresponding measurements are interval length, fuzzy membership, standard deviation, entropy of probability distribution, and range of uncertainty set. For example, the sensitivity of the objective function to the prediction variance of wind power or photovoltaic output can be used to measure the uncertainty reduction in the scheduling model of controllable load, wind power, photovoltaic, energy storage devices, and other resources. With appropriate data value evaluation and a suitable market mechanism, reasonable data pricing can be established. The data pricing mechanism based on the VCG (Vickrey–Clarke–Groves) mechanism, which is mainly used in the mechanism of the power trading market, can be adopted in the fully competitive data trading market[156]. Wang et al. proposed a fair bargaining algorithm of big data transaction based on vector evaluate genetic algorithm[161], in which the problem of data trading is modeled as a multi-attribute negotiation problem, and a novel utility function is used to determine the correlation degree among different attributes. Wang et al. used the standard deviation of load forecasting error to measure uncertainty and obtained the explicit formula of data value based on the value link of "data acquisition → uncertainty reduction → profit increase"[162].

In terms of data right confirmation, a popular method is expert review[163], but it is difficult to ensure the fairness of this method. Digital watermarking technology is a better and more robust alternative because it is difficult to be perceived or tampered with and can resist various forms of data attacks[164].

When it comes to preserving privacy in smart grids, cryptographic methods such as homomorphic encryption, Paillier encryption, and secure cryptographic hash function are widely used[165]. Differential privacy approaches like point-wise differential privacy with Laplacian noise are also used in smart grids to ensure privacy[166]. A trading model based on blockchain was proposed to perform safe and fair trading through transparent regulation. The model deploys smart contracts to independently execute trading behaviours among traders, handle trading disputes, and facilitate payment to respective traders.[151].

2.5 Digital twin

Originally developed by Grieves in 2003 as an information mirror model to improve industrial manufacturing processes[167], digital twin (DT) presents a virtual counterpart of an object in the real world built from a physical model, sensor data, historical operation data[168], and it offers a pathway for the deduction and control of real objects by digital techniques. Regarding the concept of DT, researchers usually refer to a high-tech system composed of virtual entity, physical entity, and virtual-physical connection. To realize such a DT system, a virtual environment would need to be constructed, which would require five technologies: predictive simulation, data analytics, machine modeling, artificial intelligence, and visualization techniques. Additionally, sensors, state monitoring, extended reality, edge computing, and intelligence actuation would need to be implemented in the physical environment[169]. DTs provide better insights to monitoring, understanding, and optimization on physical entities[170], which can also help reshape energy and transportation systems. Figure 2 shows the supportive technologies and ideas of DT and its main applications in the field of energy and transportation.

Energy applications

Electric companies have long attempted to use the DT paradigm to manage power systems. General Electric Co. GE used DT to optimize the whole process of wind farm development, operation, and maintenance to improve the plant's profitability and sustainability[171]. Siemens created an asset and operation management system as a DT model for Fingrid, Electrical Verkko Information System, which connects a network model and measurement database automatically via an interface[172]. Additionally, Xu et al. suggested that DT technology can help search and analyze cost-effective approaches to power plant smart management and presented a specific example of a 320-MWe coal-fired generating system[173].

For protection and maintenance (PM), Pileggi et al. considered

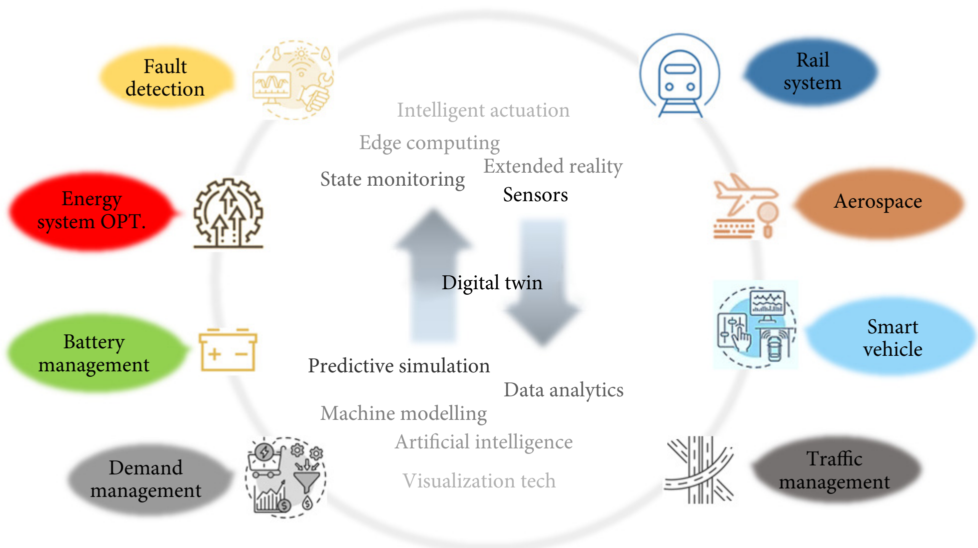

Fig. 2 Supportive technologies and theories of digital twin and its main applications in the field of energy and transportation.

DT in the anomaly detection and analysis of energy deployment, viewing the DT paradigm as an application of cyber-physical energy systems[174]. Jain et al. designed a fault detection and diagnosis procedure under DT settings to construct distributed photovoltaic systems[175]. Monitoring and controlling battery systems using DT have gained much attention, with various researchers offering insights into battery management systems in terms of overall solution design and cloud-side analysis[176–179].

In consumer-end demand management, O'Dwyer applied DT technologies to predict and dispatch regional energy assets, which enables local governments to manage energy efficiently[180]. A DT based method was proposed by Fathy to track and flatten the energy usage level to improve energy efficiency[181].

Transportation applications

The main application areas of DT in transportation are in the fields of rail systems, aerospace, smart vehicles, and traffic management. DT based solutions are applied in rail systems for evaluating and avoiding failure.

Kaewunruen et al. proposed a life-cycle assessment process consisting of material production, material transportation, operations maintenance, and demolition phases to realize the resilience and sustainability objectives in metro station systems[182]. To reduce the outage of electric railway power systems, Ahmadi et al. proposed a DT based architecture across the equipment and system levels[183].

A series of studies have laid the groundwork on the application of the DT concept and paradigm to vehicle security and safety. Barosan et al. proposed a DT model of autonomously driving trucks for a distributed auto-driving system, which offers excellent performance in testing and validating duties in various automotive scenarios[184]. An advanced driver assistance system featuring lane change prediction was realized by adopting both camera images and DT based auxiliary information from the cloud. With the help of virtualization through DTs[185], implementation methods were designed reducing for reducing auto-driving security vulnerabilities[186,187]. DT-based penetration tests in cyber-physical systems have the potential to identify and fix vehicle vulnerabilities[188–190]. It is noteworthy that massive machine learning methods[191–193] and deep learning methods[194–198] have been developed for intrusion detection in the cyberspace of DT.

With the rising number of road accidents and explosively growing data, DT based traffic management has attracted strong interest. To reduce traffic congestion, many researchers have applied DT to driver intention prediction[199,200]. Wang et al. developed a vehicle-to-cloud driver assistance system based on logical construct from DT for connected vehicles[201], so that transportation system can be more mobile and efficient. In consideration of DT, Khosroshahi et al. made use of the 3D trajectories of running cars and the prevalent recurrent network (long short-term memory, LSTM) to improve activity classification[202].

Digital twin in energy and transportation systems

The future of transport progress cannot be separated from the fast development of electric vehicles. With the improvement on testing and diagnostic technology related to electric drive systems, the proportion of electric vehicles in use in society is on the rise. Venkatesan used intelligent digital twins for permanent magnet (PM) synchronous motor health monitoring and prediction. To calculate the remaining PM life, neural network method and fuzzy logic theory were adopted to map the input distance, EV travel time, output case temperature, winding temperature, bearing lubricant replenishment time, and flux decay rate[203].

Algorithms of digital twin

Both traditional and deep machine learning algorithms are used in DT. Traditional machine learning algorithms consist of SVM, RF, etc., whereas deep methodology involves LSTM, auto-encoder, etc. With the progress of traffic technology, traffic accidents occur frequently due to driver distraction or problems with the car while in motion. For adaptive network intrusion detection, a two-layer detection approach in proposed combining C5.0 decision tree in layer 1 and a naive Bayesian method in layer 2, so as to promote the rates of detection and false alarm respectively[191]. To decrease running time of an intrusion detection application, Khammassi et al. designed a search strategy that was based on a genetic algorithm and adopted logistic regression to determine the best subset of features[192]. Hasan et al. developed two models, one based on SVM and the other using RF, as a way to determine an effective and robust intrusion detection method[193]. To address issues with networked intrusion detection systems, Shone et al. adapted deep auto-encoder to non-symmetric mode for signature learning and the stacked autoencoders were used as a deep classifier[195]. Berndt et al. used a hidden Markov model to make inferences about early driver intentions and created an advanced driver assistance system that collects information about driver behaviour earlier and more accurately[199]. Khosroshahi et al. developed a road vehicle activity classification framework for the behavior analysis of vehicles around self-driving cars by combining three-dimentional trajectory knowledge and LSTM models[202].

3 System-level impacts of digitalization

3.1 Shaping energy systems

As previously mentioned, the information network composed of high-end information technologies like 5G, IoT, cloud computing, blockchain, data trading as well as digital twin could lay a solid foundation for the digitalization of energy and transportation systems as a whole, including the processes of energy generation, supply, storage, and consumption and smart transportation management.

Distributed energy system

In contrast to centralized energy systems, distributed energy systems produce and supply energy locally. As energy consumers become prosumers and the one-way power transmission mode changes into the two-way mode, it becomes more dynamic and uncertain to operate the energy system. Challenges to the management of such distributed energy systems can be tackled by exploiting advanced technologies available in the digital age.

The continuous development of distributed energy resources (DERs) can drive the traditional power system into a more efficient and low-carbon grid[204], while IoT and blockchain can facilitate the development and operation of DERs. Wu et al. explained how the IoT promotes the interactive digitalization of the power grid so as to realize the integration of heterogeneous resources[205], and they discussed how the blockchain can change the basic transaction mode of energy transaction from a centralized to a decentralized structure and help realize multi-mode P2P energy transactions for DERs.

Distributed renewable energy is key to improving rural energy access. China's poverty alleviation through distributed photovoltaics is booming, but the operation and maintenance are challenging in many rural regions, which seriously compromises the poverty alleviation effect[206]. Digital technologies could effectively solve this challenge. By building a distributed photovoltaic power station on the cloud side for operation and management, LongShine Technology, a company for digital energy, connects photovoltaic power stations to the cloud by means of IoT, realizes digital operation and maintenance, and provides professional operation services for farmers, which greatly improves power generation efficiency and creates more income. Zheng et al, used the fuzzy analytic hierarchy process to establish a structural model and raised a regional intelligent mode to better determine the operation and maintenance of photovoltaic power stations, which provides a new approach to the development of distributed photovoltaic[206].

Table 1 summarizes the various algorithms used in the aforementioned mechanisms along with their applications in the energy and transportation systems. It includes both learning-based algorithms, involving traditional machine learning, deep learning and reinforcement learning, and optimization-based algorithms.

The evolution of algorithms shows a trend of decentralization. First, more and more distributed algorithms, like the distributed consensus algorithms employed in blockchain, emerge with big data. Second, with the rapid development of energy transportation system, more resources can be dispatched, bringing complex models with massive amounts of data. The ever-expanding scale of data generated in the process, in turn, requires parallel and distributed computation. Finally, as the energy and transportation system shift from a centralized structure to a distributed form, a new need for a distributed solution to optimal resource allocation arises, which forces the transformation of algorithms from centralized to distributed.

In addition, since the system contains vast amounts of data, more attention must be directed to the security and reliability of algorithms. On the one hand, data from energy and transportation systems inevitably entail a large quantity of private information, the sensitivity of which places higher requirements on the security of algorithms; on the other hand, energy and transportation systems involve pillar industries such as power industry, so the need for system stability requires algorithms to be more reliable.

Energy decision-making and management

Intelligent energy management systems (EMSs) enable standardized, scientific, and information-based energy management. EMSs

Table 1 Algorithms.

Mechanism	Reference	Algorithms	Algorithm category	Application
IoT	ref. [79]	Adaboost	Traditional machine learning	Transportation safety
	ref. [89]	BN-SARIMA	Time-series analysis	Traffic prediction
	ref. [90]	Hidden Markov Model	Traditional machine learning	Judging vehicle motion trajectories
	ref. [91]	SVM, MRF	Traditional machine learning	Parking system
	ref. [207]	Decision trees	Traditional machine learning	Predicting traffic congestion
	ref. [92]	Regression tree	Traditional machine learning	Predicting traffic circulation
	refs. [93, 94]	Clustering	Traditional machine learning	Traffic data simulation, Road Anomaly detection
	ref. [80]	CNN, deeper CNN	Neural networks	Road condition detection
Cloud computing	ref. [104]	Routing algorithm (Martins and meta-heuristic)	Optimization	Low-carbon transportation
	refs. [208, 209]	PSO algorithm	Optimization	Energy system optimization
	ref. [113]	QCNN algorithm	Neural networks	Low-carbon supply chain
	refs. [115, 116]	Reinforcement learning algorithm based on PSD	Reinforcement learning	Intelligent transportation
Blockchain	ref. [135]	Proof of concept	Distributed optimization	A local energy market simulation model
	ref. [137]	Proof of work	Distributed optimization	Local EVs electricity trading market
	ref. [136]	Proof of stake	Distributed optimization	A P2P energy trade platform involving auction
	ref. [125]	Proof of stake	Distributed optimization	A secure and private ITS
Data trading	ref. [162]	Parametric estimation, non-parametric estimation	Traditional machine learning	Data valuation
	refs. [161, 210]	Genetic algorithm	Optimization	Data pricing
	ref. [211]	Optimal estimation algorithm	Optimization	Data pricing
	ref. [212]	Multi objective optimization	Optimization	Data pricing
Digital twin	ref. [191]	Decision Tree C5.0, the Naive Bayes algorithm	Traditional machine learning	Vehicle intrusion detection
	ref. [192]	Genetic algorithm, logistic regression	Traditional machine learning	Vehicle intrusion detection
	ref. [193]	SVM, RF	Traditional machine learning	Vehicle intrusion detection
	ref. [195]	Auto-encoder	Neural networks	Vehicle intrusion detection
	ref. [197]	CNN, RNN	Neural networks	Vehicle intrusion detection
	ref. [198]	RANet	Neural networks	Vehicle intrusion detection
	ref. [199]	Hidden Markov model	Traditional machine learning	Driver intention prediction
	refs. [200, 202]	LSTM	Neural networks	Vehicles trajectory analysis, Driver intention prediction

can be combined with AI, big data, DT, and other technologies to realize intelligent monitoring, real-time coordination, and scheduling[213]. The EMS of a virtual power plant (VPP) based on digital technologies can coordinate and control multiple DERs (such as power generation, storage, and controllable demand) to improve local energy efficiency and stability. It can also reduce the pressure on the central energy system from the increasing number of DERs with the support of digital technologies[214].

A recent focus of sustainable energy efficiency improvement is innovative energy services based on intelligent recommendation system and DT[213]. Based on artificial neural network (ANN), gradient enhancement, and K-means clustering algorithm, a tool integrating DT and energy management was developed for providing prediction, scheduling, optimal control, and coordination services for multi-vector smart energy systems, so as to realize optimal decision-making under user-defined objectives[180]. The strong predictive power of DT technology for integrated energy systems can enable efficient coordination between energy vectors, which can significantly reduce the system cost[215].

Energy security

Energy security is a multifaceted issue involving national security and the international energy supply chain[216]. Therefore, a hierarchical distributed security and stability control strategy based on IoT that not only ensures energy security but also realizes the economic utilization of energy was proposed[217]. AI based energy system fault detection and diagnosis methods have also been shown to have great potential[218].

In summary, carbon emission reduction and digitalization are the biggest driving forces for the reform of energy systems in the future. Although IoT has been combined with energy systems, there is still much room for development and progress. In the future, we should actively promote the innovation of energy technology, information technology, and digital technology to accelerate the transformation of energy systems, optimize energy structures, improve energy efficiency, improve energy governance, and promote energy transformation and high-quality energy development.

3.2 Shaping transportation systems

Smart vehicular network (SVN)

Smart vehicular network (SVN) is an important application of IoV in which the road/vehicle sensors and smart traffic lights are integrated[219]. These sensors could make communications with smart traffic lights along the road and manage all generated data efficiently. Details from multiple traffic lights are collectively connected and forwarded to the cloud to provide a broad perspective of traffic in a given area[219]. IoV and autonomous driving technologies can be combined to shape future low-carbon transportation systems[220–222]. Connected autonomous vehicles can share information to alleviate traffic and parking congestion[220,223,224] and reduce traffic accidents[225]. The combination of autonomous vehicles with ride-sharing can also alleviate congestion by reducing the number of vehicles on the road[226] and lowering the average service time[227], which can also cut down on energy consumption and carbon dioxide emissions[228–231].

Transportation data security

In the near future, all vehicles will be connected with smart devices via the Internet, which will generate mass of data on different servers. Specifically, in the application scenario of IoV and autonomous driving, a large amount of private data of vehicle drivers, such as route, home/work address, and schedules. The wide interconnection will present a privacy risk since the information of vehicle users could be leaked[232]. Blockchain technology delivers a promising approach for addressing privacy problems in ITSs[233,234].

3.3 Energy and transportation integration

Transportation sector decarbonization entails transportation electrification, either directly or indirectly. In this context, energy and transportation systems are becoming more closely integrated through EV charging, vehicle-to-grid (V2G), mobile charging stations, and the information network, as shown in Figure 3. The left side of the figure shows the application scenario of the smart grid, and the right side of the figure shows the application scenario of the ITSs.

EVs are the product of the coupling of energy and transportation, and as technology advances, more and more technologies are applied to the field of EVs. For example, the electric drive system of EVs is embedded with current sensors, voltage sensors, etc[20]. The smart car integration system is established through 5G/6G to oversee the smart energy management level of smart EVs, whereas the Internet of Things is also used to monitor and make predictions for EVs[36]. In the V2G field, IoT technologies are widely employed, and numerous methods are proposed to improve the electric efficiency of EVs as well as its grid stability[235,85]. In applications such as EV-to-grid and micro-grid, blockchain technology can provide necessary information to assist in grid management and control[132,133]. Data trading can be adopted in EV applications to more effectively regulate the imbalances between energy demand and energy supply[154]. Digital twins can be used to diagnose and predict failures in electric vehicle power systems, etc[203].

Integration by EV charging

Electrified transportation is booming. The coupling of energy and transportation systems has been deepened and linked mainly by EVs and charging infrastructure[236,237]. Recent studies pertaining to the interdependency of energy and transportation systems mainly focus on the planning and operation of the two systems[238]. The structure of the transportation network, the demand distribution, and the driver behavior have to be considered in the planning of charging stations. Conversely, the planning of charging stations affects the transportation system by changing the charging behavior of EV drivers[239]. Many works have considered the coupling effects between energy and transportation systems in the planning problem[240–242]. In the operation problem, the loads of charging stations are relevant to real-time traffic flow. The location, availability, and charging price of a charging station can affect the convenience of transportation[243–245].

Digitalization can undoubtedly reinforce the integration of energy and transportation systems[244] and promote the efficiency of integrated systems. Digital technologies make it very convenient to obtain and utilize the information of charging stations and traffic conditions. Zhou et al. investigated the effects of EV drivers choosing the lowest-cost routes according to the real-time charging price and traffic conditions from a game theory perspective. Furthermore, it was shown that power consumption would be reduced and traffic congestion would be alleviated[246]. Qian et al. proposed an EV navigation method based on deep reinforcement learning to minimize two objectives of the total travel time and the charging costs[247].

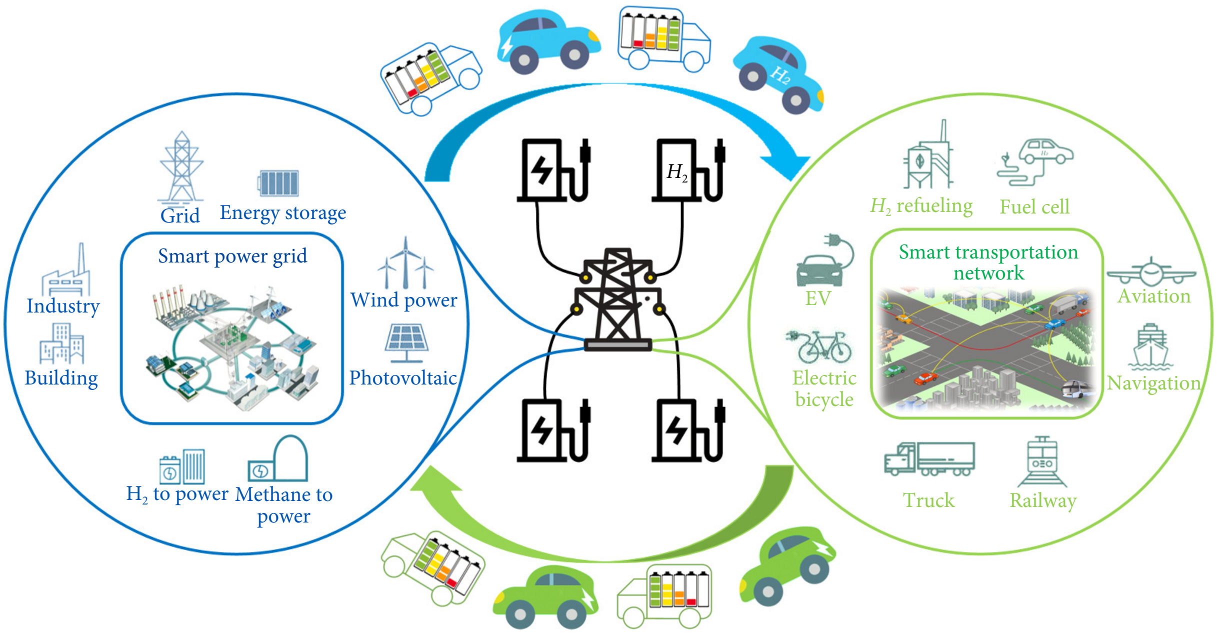

Fig. 3 Schematic of future integrated energy and transportation systems.

Integration by mobile charging station & V2G

Because of the small ratio EVs compared to internal combustion engine vehicles, investing in a lot of charging stations at all locations is not financially viable. As an alternative, mobile charging stations can make a difference in accelerating EV adoption by offering portable charging services for EVs at convenient times and locations[248,249]. Khardenavis et al. proposed a framework for planning mobile energy hubs with automatic charging and discharging taking the temporal variation of charging demands into consideration[250].

The on-demand operation of mobile charging stations can be further optimized based on IoV. V2G has been discussed for decades, through which the transportation system supports the energy system by responding to varying demand and renewable energy generation[251–253].

3.4 Carbon footprints

Carbon emissions estimation

Traditionally, input-output modeling[254] and life cycle assessments[255] have been commonly used for carbon emission estimation. The environmental impact or carbon footprint of power supply is often analyzed through a life cycle assessment using greenhouse gas emission factors. As penetration of renewable energy resources increase in the electricity grid, the future carbon footprint of the energy system will become more variable, on both the supply and demand side[256]. Seasonal and diurnal fluctuations will increase, and overall emission factors will decrease. Considering this scenario, the effects of flexible resources like demand-side management, efficiency measures, and the expansion of renewable energy resources on emissions must be examined in detail with dynamic emission factors[257,258]. Braeuer et al. proposed the use of dynamic emissions factors in hourly resolution to utilize energy storage systems to reduce the carbon footprints of energy intensive industries and power systems[259]. Other researchers have studied the use of dynamic emission factors to evaluate charging strategies of EVs to minimize life cycle emissions[260,261]. Although studies on how digital technologies will influence the evaluation of emission factors are few, existing studies have demonstrated that with the development of advanced monitoring systems in power systems and industry, more data are becoming available for precise emission factor estimation with detailed resolution.

Carbon emissions trading system

Carbon emissions trading is a market-based mechanism considered to promote the reduction of emissions of greenhouse gases, such as carbon dioxide, under the *Kyoto protocol*[262]. Many countries and regions, particularly Europe, North America, and Asia, are developing their carbon emissions trading systems. In China, allowances of emission rights are allocated to emission producers according to projected emission levels[263]. Penalties on excess emissions are set relatively high to enforce emission control. Producers with abundant emission rights can sell their allowances to earn profits. Launched in 2005, the EU emission trading system was primarily designed to achieve cost-minimal target under a given emission budget. Now it is the world's first and biggest major carbon market[264].

Explorations on emissions trading systems have shown it is effective to trade carbon emissions under the market environment[265]. However, emissions trading systems still face certain problems, such as emission quota allocation and certification and transaction of emission data. Under the current carbon emissions trading system, carbon allowances are too complex to allocate because of different requirements from different regions and countries. For global emission control and management, there is still no unified carbon trading system able to coordinate different policies and thus improve the efficiency of the carbon trading system[266]. As digital technologies develops, especially blockchain technologies, emissions trading systems could enter into a generalized trading market with unified carbon allowance and prices, and achieve a decentralized trading structure[266]. Under the decentralized trading structure enabled by blockchain technologies, small carbon emitters could participate in the market, thus incentivizing more carbon emission reduction.

4 Challenges and future directions

4.1 Sensors

Though sensors and embedded systems are mostly designed based on low-cost technologies for massive and wide applications, which brings great advantages in economic and engineering aspects, they suffer from reliability and maintenance problems[267]. Computational and machine learning techniques can be applied to sensor design to improve reliability[268] or detect potential failures or attacks[269]. Future directions also include optimizing the placement of sensors in integrated transportation and energy systems to maximize the utility of collected data.

4.2 Blockchain

Although many blockchain projects and research initiatives have shown that blockchain is a promising technology capable of addressing challenges like distributed energy generation[270] and micro grid development[271] in the energy sector, there are still several problems that need to be solved before industrial adoption[120]. First and foremost, the scalability, speed, and security of blockchain need to be validated in practice. To improve the performance of consensus algorithms, more research is still required to attain both scalability and security of consensus algorithms, both of which are critical to establishing real practices. Additionally, it will be necessary to identify optimal trade-offs among scalability, speed, and security[138,272]. Second, blockchain communities are extremely susceptible to security risks due to a poor structural design or malicious attacks, especially when scaling up[120,273]. Blockchain applications in energy and transportation systems in the early stages will face additional risks because they largely rely on the creation of new algorithms, a process where errors are common. In addition, there is a good chance that blockchain will be attacked before the technology becomes mature enough for practical applications. As a result, public opinion may not be favorable. Another challenge from an economic perspective is the high-cost investment in blockchain-based applications. In contrast to well-established solutions like relational databases, blockchain technology requires investment in expensive new infrastructures, such as smart meters in power grids and corresponding software development, of which the costs need to be balanced against the benefits in terms of data integrity, enhanced security, and elimination of the need for a trusted intermediary[120]. Such benefits, however, may also be hard to quantify.

4.3 Digital twin

Due to the complexity and dynamic nature of the energy and transportation systems, there are still a few challenges hindering the improvement and application of DT in both sectors. Challenges and future requirements mainly involve the improvement of general DT infrastructure such as GPU and IoT device, safety and security, signal processing and connection, accuracy of modeling, moral principles of AI application, and easier implementation[169,274–278]. With the aid of a DT system, it will be more convenient to carry out a sequence of work for the physical entity, such as planning, sensing, operating, analysis, pre-diagnosis, and so on. In addition, there will be more DTs for a deeply integrated energy and transportation system, which could achieve low-carbon transportation. DT could also enable easier integration and coordination of other industrial sectors or supply chains with energy and transportation systems, such as manufacturing, the atmosphere, and ocean systems[182,183].

4.4 Data trading

Data trading in low-carbon energy and transportation systems is in the initial stage at present. The key challenges include right confirmation, pricing, security, and privacy protection[141,143,144]. No countries have yet stipulated the rights of data by clear laws and regulations, so the legal risk is a major obstacle to data trading. Another problem is the lack of feasible general data pricing models. Additionally, accidental breaches of data security and privacy occur frequently. Effective supervision mechanisms and service systems are needed to ensure the security and compliance of data trading. Data in a low-carbon energy and transportation system can be time-sensitive, necessitating more efficient trading mechanisms and algorithms.

Data trading will further strengthen the connection between energy and information, thus improving energy efficiency and increasing the value of information transmission. In the future, the collaboration between academia and industry will be essential for the advancement of both theoretical research and industrial implementation. Since data trading is closely tied with the actual scenario and requires a market for demonstration, related large enterprises should be encouraged to carry out pilot work, through which they can tap into the potential of existing industry data and focus on the practical problems of data trading.

4.5 Transportation systems

After discussing the difficulties with infrastructure and mechanisms in the previous subsections, we will now turn to the challenges that transportation and energy systems face.

The biggest digital challenge in transportation lies in the area of smart transportation. To enable closer relationships between transport systems and users, future ITS may need to deploy road networks to share and control information, allowing vehicles to connect with roadside devices when necessary to keep track of upcoming road conditions or other important notifications, like lane clearing for public transport or emergency vehicles. However, attackers may target open communications to eavesdrop, modify, insert forged (or malicious) messages or delete any data without considering the security, validity and system latency of user data[279]. Existing researches have introduced blockchain technology to solve such problem, although less attention has been paid to blockchain security and the latency it brings. Still, many other factors must be taken into account if the problem is to be solved in the future[280].

In addition, there are other difficulties brought on by the development of the V2G model. One major challenge is the additional battery degradation incurred by the repeated charging and discharging cycles of bidirectional V2G implementation[281]. For the convenience and safety of their vehicles, drivers of electric vehicles usually charge in advance or ensure high charging levels for their electric vehicles[282], which would preclude them from actively participating in two-way V2G services. Future researches should focus on intelligent scheduling and valuation technologies of V2G as well as digital battery management technologies.

4.6 Energy systems

Digitalization in the energy sector primarily provides the necessary infrastructure and interfaces to support the functional and efficient operation of businesses by operators. With generation decentralization, infrastructure digitization, intelligent control and engineering, digitalization will, in the future, become the main tendency in the energy sector. An important digital trend in the energy sector is the transition into a smart grid, which allows the processing, control and management of massive data flows[283].

4.7 Integration of energy and transportation systems

The main purpose of applying digital technology to EVs is to produce intelligent EVs that can connect with massive amounts of data. These vehicles have data throughput capacities, computing speeds, and built-in cloud connection environments that are significantly higher than traditional cars, and are unparalleled in terms of response speed, redundancy expansion, power carrying, space arrangement, and other aspects compared with traditional vehicles[284].

Secondly, there are still many challenges in terms of privacy and security for EV data. The frequent communication between EVs and the grid for co-optimization gives the grid operators access to EV driver information, such as home and work addresses, occupation, and health status[285]. However, to the best of our knowledge, few studies have focused on the privacy and security of energy and transportation systems. Data structures and interfaces also need to be unified within and across energy and transportation systems to enhance interoperability for co-optimization. Another problem to be solved is that the time resolution could be different for different applications.

As autonomous driving technologies develop, opportunities emerge in the coordination of autonomous driving, energy flow, and carbon footprints, which can be realized in a distributed manner with the support of IoV, 5G/6G infrastructure, and edge computing.

4.8 Low-carbon computing

It is speculated that nearly 50 billion IoT devices will exist by around 2025[286], and the energy consumption of digital technologies and computing will be significantly higher, possibly over 10% higher, compared to the previous decade. In this context, it will be critical to coordinate the data flow, energy flow, and carbon flow in a cost-effective manner with digital technologies. Such spatio-temporal multi-flow coordination will involve renewable generation forecasting, cyber-physical system planning, computing routing, and cross-regional network and data center planning.

5 Conclusions

From sensors to 5G, IoT to data trading, digital technologies are making the energy and transportation systems more efficient, sustainable, and intelligent. In the trend of digitalization for decarbonization, both barriers and opportunities exist, which calls for deep collaborations between academia and industries as well as among different industry stakeholders. For policy makers, on the one hand, incentives or mechanisms for data sharing and trading should be better designed to provide explicit benefits for collaborative digitalization across energy and transportation sectors. On the other hand, protecting data privacy and security as well as data right requires technologically informed regulation design. Only with balanced regulations, the digitalization shall be a boon not a bane.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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