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Recent advances on industrial data-driven energy savings: Digital twins and infrastructures

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ABSTRACT

Data-driven models for industrial energy savings heavily rely on sensor data, experimentation data and knowledge-based data. This work reveals that too much research attention was invested in making data-driven models, as supposed to ensuring the quality of industrial data. Furthermore, the true challenge within the Industry 4.0 is with data communication and infrastructure problems, not so significantly on developing modelling techniques. Current methods and data infrastructures for industrial energy savings were comprehensively reviewed to showcase the potential for a more accurate and effective digital twin-based infrastructure for the industry. With a few more development in enabling technologies such as 5G developments, Internet of Things (IoT) standardization, Artificial Intelligence (AI) and blockchain 3.0 utilization, it is but a matter of time that the industry will transition towards the digital twin-based approach. Global government efforts and policies are already inclining towards leveraging better industrial energy efficiencies and energy savings. This provides a promising future for the development of a digital twin-based energy-saving system in the industry. Foreseeing some potential challenges, this paper also discusses the importance of symbiosis between researchers and industrialists to transition from traditional industry towards a digital twin-based energy-saving industry. The novelty of this work is the current context of industrial energy savings was extended towards cutting-edge technologies for Industry 4.0. Furthermore, this work proposes to standardize and modularize industrial data infrastructure for smart energy savings. This work also serves as a concise guideline for researchers and industrialists who are looking to implement advanced energy-saving systems.

1. Introduction

Throughout the timeline of manufacturing and processing, there were certain incredibly novel technological breakthroughs which flourished the possibilities of a new system, and even, a new manufacturing era. The first occurrence of such ground-breaking technology happened in 1763 where James Watt invented a version of the steam engine which was incredibly fuel-efficient at that time [1]. This key piece of technology opened the doors towards the first industrial revolution which relied on the principles of the thermodynamic engine and mechanical gear. A reoccurrence of this phenomenon of industrial revolution happened in the 19th centuries where many new technologies, especially electricity, were invented [2]. The acquisition of electricity and electrical applicants in this time of history allowed for mass production of daily products, giving birth to the start of a new economy. This was the second industrial revolution. Further development of electronics in the next hundred years had advanced both the energy industry and utilization of electronics, leading to the third revolution. Most notably, the transition from oil and gas to utilizing nuclear and bioresources as energy sources [3] has drastically changed the economy. In the industry, the extensive use of automation also emerged due to the invention of programmable logic control (PLC) and simple robots [4]. Today's enabling elements, which include Artificial Intelligence (AI),

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Nomenclature

AI	Artificial Intelligence
AMO	Advanced Manufacturing Office
APC	Advanced Process Control
BI	Business Intelligence
CAD	Computer-aided Design
CFD	Computational Fluid Dynamics
CHP	Combined Heat and Power Plant
CNC	Computer Numerical Control
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
CPU	Central Processing Unit
CVD	Chemical Vapour Deposition
DaaS	Data as a Service
dApps	Decentralized Applications
EMEA	Europe, the Middle East and Africa
ERP	Enterprise Resource Planning
EU	European Union
FEA	Finite Element Analysis
GB/s	Gigabytes per seconds
GPU	Graphics Processing Unit
HMI	Human Machine Interface
HVAC	Heating, Ventilation and Air Conditioning
IaaS	Infrastructure as a Service
IIoT	Industrial Internet of Things
Industry 4.0	Forth Industrial Revolution
IoT	Internet of Things
IP	Intellectual Property
IP69k	International Electrotechnical Commission's protection rating for Dust Tight and Able to Sustain High Pressure Cleaning or Steam Jet
ISO	International Standard Organization
IT	Information Technology
KPI	Key Performance Indicator
LCA	Life Cycle Analysis
MES	Manufacturing Execution System
MYR	Malaysian Ringgit
NDRC	National Development and Reform Commission
NEA	National Energy Administration
OII	Open Innovation Intermediaries
PaaS	Platform as a Service
PASPO	Principal Component-aided Statistical Process Optimization
PAT	Perform Achieve and Trade scheme
PLC	Programmable Logic Control
PwC	PricewaterhouseCoopers
QR	Quick Response
R&D	Research and Development
RB-FEA	Reduced Basis Finite Element Analysis
RFID	Radio-frequency Identification
RTU	Remote Terminal Unit
SaaS	Software as a Service
SCADA	Supervisory Control and Data Acquisition System
Sim-to-Real	A field of artificial intelligence dealing with transferring simulation to the real world
SPP	Standard Payback Period
SVM	Support Vector Machine
TEE	Trusted Execution Environment
TOE	Tonnes of Oil Equivalent
TPU	Tensor Processing Unit
UI	User Interface
UPS	Uninterruptable Power Supply
USD	United States Dollar (Used synonymously with "$")
UX	User Experience

advanced robotics, cyber-physical production systems (CPPS), internet of things (IoT) and Big Data [5], is leading to another new revolution. Industry 4.0, also known as the fourth industrial revolution is the idealization of an economy that produces materials or provide services with highly automatized procedures [6].

In advanced countries, such as Germany, France, Japan [7] and China [5], Industry 4.0 projects related to autonomous processing, operational improvement and energy-savings have been increasing steadily. However, World Economic Forum [8] reported that only 25 countries within the world are ready to benefit from the changing nature of Industry 4.0, which are (in alphabetical order) Austria, Belgium, Canada, China, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Isreal, Italy, Japan, Korea Republic, Malaysia, Netherlands, Poland, Singapore, Slovenia, Spain, Sweden, Switzerland, United Kingdom and United States. Furthermore, researchers such as Rajnai and Kocsis [9] had shown that there are significant labour market risks associated with Industry 4.0. Nevertheless, the values derived from transitioning to Industry 4.0 is too much attractive for both the micro- and macro-perspectives in terms of resource conservation, asset utilization, labour allocation, inventory management, quality improvement, supply-demand matching, time-to-market management and aftersales service [10]. In this case, much more developments are required to achieve Industry 4.0 in various parts of the world. In terms of research effort, Preuveneers and Ilie-Zudor [11] pointed out that more works have to be done on end-to-end production transparency, information management in industrial systems, optimization of industrial processes with Big Data and cloud computing, production-aided with machine learning, human-computer and machine interaction, security threats and regulations. Zhou et al. [5] also highlighted that the challenges of transitioning to the Industry 4.0 contain complex aspects of scientific challenges, technological challenges, economic challenges, social challenges and political challenges. On the production floor level, Weyer et al. [12] demonstrated the importance of infrastructure standardization with examples related to electro-mechanical standards, production lines, communication standards, control architectures, work stations and integration of superordinate IT systems.

Energy savings is one of the most attractive targets to achieve improved energy efficiencies with the technologies of Industry 4.0 [13]. Song and Wang [14] proposed a data-driven measuring method to consider technological progress for energy saving and emission reduction in the settings of Industry 4.0. An energy management system named Energy Cloud [15] was also deployed to monitor energy consumption in multiple industrial sites by utilizing Big Data and cloud computing. Lee et al. [16] argued that deploying a self-aware machine within the context of Industry 4.0 could also reduce processing cost by saving energy consumption. From a project implementation perspective, Oses et al. [17] proposed using a statistical learning approach to measure and verify energy savings within an industrial plant. The model was able to act as a baseline energy-saving model while reducing uncertainties in real-time. Furthermore, Wang et al. [18] proposed a four-level architecture for energy-saving operations which includes a physical and sensible manufacturing system, system unit models in virtual space, system production model in virtual space and active energy-saving operation decision model. By utilizing an intelligent information processing approach, Yan et al. [19] argued that the intelligent factory can improve system reliability from applying predictive maintenance and intelligent energy savings.

To demonstrate the importance of industrial energy savings from a regional viewpoint, the European Council emphasizes to reduce projections of primary energy consumptions in 2020 by 20% [20]. The European Commission also adopted a roadmap up to 2050 to focus on low carbon economy with a focus on energy efficiency [21]. United States Department of Energy also established the Advanced Manufacturing Office (AMO) to improve the energy and material efficiency, productivity, and competitiveness of manufacturers across the industrial sectors [22]. To date (as of 2019), AMO has provided more than 1300 industrial partnerships and projects related to energy savings in the United States. In China, the National Development and Reform Commission (NDRC) and the National Energy Administration (NEA) jointly release the 13th Five-Year Plan for Energy Development with focus on optimizing energy systems, reducing energy consumption, promote renewable energy supply, promote efficient energy technology, build fair energy market system, strengthen energy cooperation and achieve energy sharing [23]. Moreover, the Ministry of Power in India [24] is reported to promote Perform Achieve and Trade Scheme (PAT) which enhances energy savings within energy-intensive industries. In the first PAT cycle, the overall energy saving achieved was 8.67 million TOE (tonnes of oil equivalent), exceeding targets by 30%. In South-East Asia, the Ministry of Energy, Green Technology and Water [25] of Malaysia have also allocated an annual budget of MYR 54.3 million (approximately 13 million USD) to improve energy efficiencies of appliances within the country. Evidently, countries around the globe prioritize energy savings and energy efficiency of industrial systems heavily, as it is critical for sustainable development on a macro-perspective.

The transition to an energy-efficient Industry 4.0 is inevitable throughout the evolution of mankind. According to PricewaterhouseCoopers (PwC) reports [26], data-driven improvements to resource and energy efficiency are expected to have an 18% increase. The report also mentioned that the data-driven industry is already generating more than 110 billion Euro of additional revenue in Europe. McKinsey & Company [27] estimates that Industry 4.0 would improve productivity in the technical profession by 45–55%. Nevertheless, in terms of realistic energy saving implementation, Máša et al. [28] demonstrated that the real challenge is in dealing with the data and processing infrastructure in existing facilities. The work also highlighted the main problem within existing firms, which is, most of them have incomplete data acquisition system. Weyer et al. [12] also agreed that data infrastructure is one of the most challenging aspects for firms to transition towards Industry 4.0. The work proposed to standardize and modularize the data infrastructure within smart production systems. Still, there is a research gap for the development of an efficient "one-size-fits-all" approach for data-driven process analysis and data acquisition for non-experts or non-professionals. Furthermore, research in this field will be strongly motivated by the (i) significance, timeliness and contribution towards Industry 4.0, (ii) international interest in providing a more energy-sustainable future, and (iii) government initiatives and policies.

In this work, Section 2.0 discusses the current state and challenges with the consideration of the conventional pipeline for data-driven energy saving. Section 3.0 discusses enabling technologies that will accelerate the research field (such as Industrial Internet of Things (IIoT), digital twins and cyber-physical systems, cloud computing, and advanced blockchain technologies). Furthermore, Section 4.0discusses policies and government initiatives that will provide subsidies or benefits for data-driven energy savings in different countries or regions. Additionally, Section 5.0 discusses the difference between the modern and traditional implementation of industrial analytics for energy savings while giving a focus on industrial-academic collaboration. Authors have also provided future directions that may accelerate the research field in Section 6.0 while the concluding remark was provided in Section 7.0.

2. Current state and challenges

The current situation of utilizing data-driven analytics for the purpose of industrial energy savings is steadily rising throughout the years (See Fig. 1(a)). From the year 2000–2018, the top ten countries that contribute the most to data-driven energy-saving research (in terms of published research documents in SCOPUS) are China, United States, Italy, Germany, United Kingdom, Iran, Spain, Canada, Russian Federation and Japan. With modern manufacturing and production system having an increasing improvement in sensors and data acquisition, data-driven analytics has grown in interests throughout the years within the context of the Industry 4.0.

There are still some undeniable gaps to be addressed by both academic researchers and industrial practitioners for data-driven analytics in the context of Industry 4.0. Kusiak [29] discussed that these challenges arise in (i) adopting strategies for information management, (ii) improving data collection and utilization, (iii) designing predictive models, (iv) managing with model uncertainties, (v) connecting factories and control processes. Mittal et al. [30] provided a concise review on the maturity model for aspects of Industry 4.0 showing that there are still many technologies that are not matured for the transition towards full Industry 4.0. In reality, Zhang et al. [31] discussed that one of the main challenges for data-driven energy savings is the complexity that arises from the variety of energy use across thousands of processes. To deal with this complexity, Shouf et al. [32] proposed the use of multi-level energy awareness to process energy data which corresponds to process level, machine level, production line level and production level. In terms of improving the energy efficiency of existing systems, Grueneich [33] laid out five critical challenges that includes: (i) the ability to support an increasing magnitude of energy efficiency savings, (ii) diversification of sources of energy, (iii) the measuring standards of energy savings must be established, (iv) energy-saving outcome must include carbon reduction framework, (v) variability of energy efficiency must be understood. To successfully overcome such challenges, strategies from technological innovation, energy market, policy framework and agency governance must be adopted.

2.1. Pipeline for data-driven energy savings

In all cases, data-driven energy-saving procedures can be classified into four steps: (i) data acquisition, (ii) data pre-processing, (iii) modelling and analysis, and (iv) industrial implementation (see Fig. 2). Even though many researchers with actual industrial experiences suggested that the real challenge of data-driven energy savings is at the stage of data acquisition [28,29,31,32], academic researchers at the current state have more research attention towards modelling and analysis. Authors suspect that this is due to the academic ecosystem viewing research related to "modelling and analysis" as trendier and more applicable. With an overload of research interest in the fields of energy modelling and analysis, other parts of the data-driven energy-saving pipeline (i.e., data acquisition, pre-processing, implementation) becomes a significant bottleneck for the field of research. There is a strong need for a concise review of the development of each part of the pipeline to realign the researcher's interest towards the industry's demands.

Data collection and acquisition is one of the most important procedure for data-driven energy savings. The quality of the energy-saving implementation is only as good as the quality of the data available. The task of data collection is a complex task which includes sensor selection, communication protocol, information systems, data warehousing, data prioritization and much more unforeseen engineering works [34]. Work from Abdelaziz et al. [35] reviewed that even for audit-based energy-saving procedures, the importance of historical energy-related database cannot be avoided. Additional data is also proposed to be obtained *via* portable data acquisition tools such as fuel efficiency monitor, clamp-on power meter, thermocouple sensor and data loggers. By considering an enterprise energy-information system, Swords et al. [36] reported that data collection is important for both energy data and enterprise data. Similarly, the work also emphasized the importance of

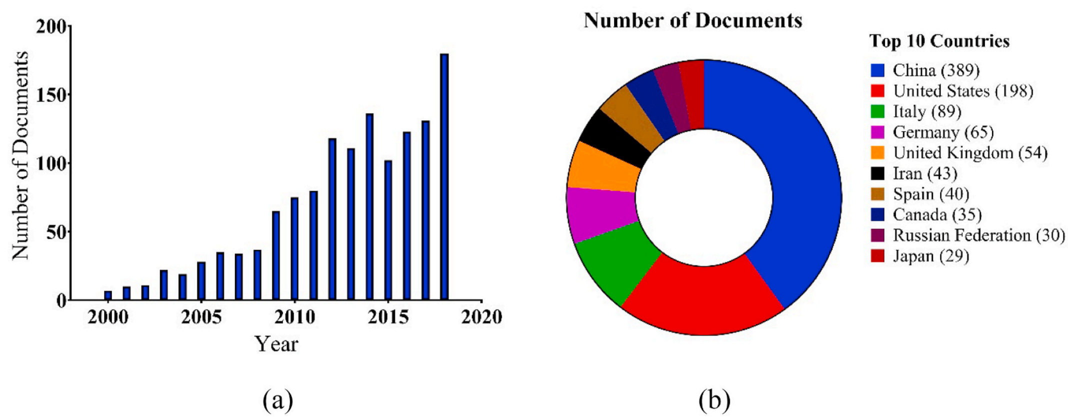

Fig. 1. Research interest of data-driven energy savings in the industry from 2000 to 2018 based on SCOPUS database: (a) Exponentially growing number of research articles (b) Top ten countries with contributing research articles. Search keyword on SCOPUS is “("Energy Savings") AND ("Industrial Process" OR "Manufacturing" OR "Production") AND ("Machine Learning" OR "Data" OR "Artificial Intelligence")”.

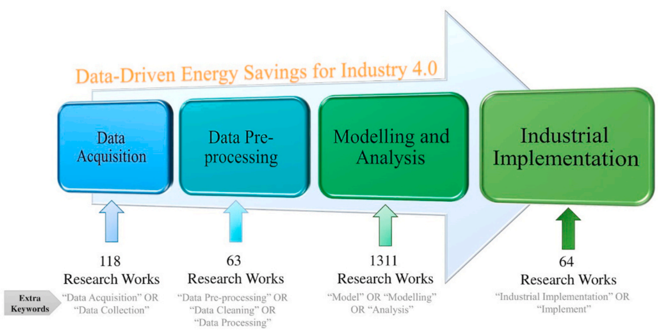

Fig. 2. The attention of research works in the data-driven energy-saving pipeline.

data collection tools while promoting the use of energy management according to ISO 140001. For energy management aspect, data collection and acquisition is critical as data-driven practices can work continuously and seamlessly to detect inefficient and malfunctioning equipment, optimize energy usage and performances [37]. Some important works related to data acquisition can be found in Table 1.

Data pre-processing is also known as data cleaning as it is the operation of converting raw data from data collection devices to useful data for analysis. Many data engineers consider the work of this stage as ‘data janitor work’. However, the industry proves that preventing “dirty data” usage is crucial for industrial energy savings [49]. Cai et al. [50] proposed 5 dimensions for the assessment of clean data which covers availability, usability, reliability, relevance and presentation quality. The work proposed a conceptual idea of utilizing indicators, data quality elements and dimensions for the phase of data pre-processing. For the application of energy-saving, the energy consumption for computing the data cleaning algorithm is often studied by researchers [51]. On the technical ground, Chu et al. [52] reviewed that advanced data cleaning procedure should be able to carry out qualitative error detection, error repairing, and adaptive data cleaning. Nevertheless, the most important purpose for data pre-processing for data-driven energy savings is on the removal of noise containing data, missing data removal and data structure unification [53]. Although there is lesser research work that relates to the “data janitor work”, its importance is undeniable, and some useful papers can be found in Table 2.

The core of the data-driven energy-saving pipeline is the procedure for modelling and analysis. Data-driven modelling has received very much attention in recent years due to its unparallel advantages in adaptability, accuracy, predictivity and simplicity [56]. Within this field, the rise of AI, digital twins and cyber-physical systems (CPS) have been pushing the boundaries of its possibilities [29,57] (this is further

Table 1
Significant works related to data acquisition and collection.

Work	Year	Contribution
Cordeau and Barrington [38]	2010	Evaluate the performance of data acquisition systems to conduct energy balance analysis in two commercial broiler barns. Discussed that better data acquisition procedure can give better results.
Januteniene et al. [39]	2012	Used an external data logger for data collection to carry out real-time process optimization using advanced process control (APC) controller to lower overall energy consumption.
Tian et al. [40]	2012	Proposed a company-level data collection methodology that relied on statistical data of local government, audit reports, and technical reports. Compared technical measures from 44 companies to assess the potential of energy-saving in a Chinese fine chemical industrial park.
Brundage et al. [41]	2013	Highlighted the importance of Energy Efficiency Performance Indicators that uses real-time production data to identify energy-saving opportunities.
Nunes et al. [42]	2014	Collected information related to facilities, equipment, technical operations and production processes from multiple refrigeration systems in the fruit and vegetable industry. Performed comparative analysis between various industrial plants of the sector.
Nunes et al. [43]	2015	Adapted a method of utilization of a combination of the industrial production database and separate technical data to gauge the potential energy savings in the dairy food sector.
Abele et al. [44]	2015	Emphasized the importance of information infrastructure for data collection to achieve energy-efficient production. The work refers to systems such as Programmable Logic Controller (PLC) and Human-Machine Interface (HMI) as prerequisites for energy Key Performance Indicator (KPI) monitoring.
Wei et al. [45]	2016	Implemented IoT-based communication framework for data collection within the processing facility and utility systems. Developed a complete energy management network to achieve energy savings
Cosgrove et al. [46]	2017	Collected data for energy savings in a holistic manner. Discussed that industrial energy can be classified as value-added energy, auxiliary energy and indirect energy. Highlighted the importance of lean energy management with consideration of value stream.
Tuo et al. [47]	2018	Propose the usage of real-time data collection to calculate energy efficiency index through “virtual part” of the machining systems.
Zhang et al. [48]	2019	Multi-attributed data related to total energy consumption were extracted from historical data to optimize machine scheduling.

Table 2
Significant works related to data cleaning and pre-processing.

Work	Year	Contribution
Miksovsky et al. [54]	2002	This work proposed a data pre-processing tool called SumatraTT. The software was tested to be able to copy data, format data, calculate new attribute, filter data, report and visualize data on the case study of a water distribution company.
Huang et al. [49]	2006	Shown the effectiveness of data pre-processing in providing a data-driven solution for a semiconductor chemical vapour deposition (CVD) process. The data pre-processing procedure focuses on data reduction, treating missing values, noise reduction and anomaly detection.
Deng et al. [51]	2018	Demonstrated that low energy in-network data cleansing algorithm can be used to pre-process data for Cyber-Physical Production System (CPPS) models.
Lenz et al. [53]	2018	Proposed a holistic approach to deal with manufacturing unit data as a whole system. Reduced the software and computational effort required to perform data cleaning to remove noise and deal with missing data.
Dai et al. [55]	2019	Pointed out that data pre-processing is crucial in noise reduction, missing value interpolation and inconsistency mitigation. Highlight the difficulties for data pre-processing, compression and storage.

discussed in Section 3.2). Data-driven methods have proven to be much superior to traditional engineering correlations and mathematical modelling methods. For example, data-driven modelling can be used to reduce the number of processes of an oil refinery with minimal background studies while mathematical programming would require thousands of equations and variable sets for optimization [58]. Leong et al. [56] also demonstrated that data-driven modelling methods can easily adapt to the uncertainties and changes within the real world, which traditional methods generally fail to achieve [59]. Neural networks were also recently grown in popularity within the ecosystem of energy savings to provide predictive analysis and highly non-linear modelling accuracy [60,61]. With rapid evolution within the field of data-driven modelling from various study disciplines, the future for data-driven energy-saving is promising. In this aspect, some of the significant works that contributed to utilizing industrial data for data-driven energy savings towards the perspective of Industry 4.0, are compiled in Table 3.

In today's world, training a data-driven model can be as easy as loading a dataset and pressing one button. Nevertheless, ensuring the model is truly useful in the real world is not presumption, the whole framework has to be properly designed meticulously for it to work [70]. There are also many hidden problems during implementation that a theoretical study will not consider. For example, inconsistency of equipment wearing in a single process [31], uncertainties in operations [71], information architecture [70], physical constraints [58] and even more unexpected problems. Researchers should favour actual industrial implementations of energy-saving solution much more than elegant theoretical mathematics as they bring much more insights and experience to the problem itself. Diving too deep into theoretical problems will only lead to producing many "garbage-in-garbage-out" models that do no good to the industry. The needs to combine industrial implementation, knowledge and data-driven modelling is a critical aspect for successful projects [28]. Tao et al. [72] pointed out that models without consideration of industrial implementation can fail to reflect in the real world, leading to poor decisions and catastrophic problems. The work provided an example of a Beijing-based company causing a steam turbine to overheat due to not including lubricant levels into its digital twin. Some works that carried-out industrial implementation for the purpose of energy savings can be found in Table 4.

Apart from operational difficulties during industrial implementation, the user interfaces and user experience (UI/UX) of the energy solution is also important. Zhang et al. [31] demonstrated that a good user interface for data visualization is effective in identifying low energy efficiency ball mills in a Chinese milling factory. Good visualization at this stage can compress complex high dimensional data into simple bar charts that are directly indicative of the priority within the process [58]. Furthermore, Lade et al. [76] argued that a visualization platform is essential for the industrial Big Data that is gathered. The work discussed the importance of data visualization for aiding engineers to obtain a lucid and comprehensive overview of the whole process system. Some ready-made tools for this purpose are available in the market, such as AWS QuickSight, Google Data Studio, Tableau and Microsoft BI which makes implementation straightforward. The upcoming sections will discuss the information infrastructure that will be hosting the data pipeline (Section 3.0), integration of advanced technologies, government policies and barrier between researchers and industrialists.

3. Industrial infrastructures and enabling technologies

Industrial infrastructure for managing the processing and operational data is generally distributed and non-unified. Data infrastructure technologies may range from QR (Quick Response) codes and RFID (Radio-frequency Identification) tags to smart machines and devices [77]. From a holistic viewpoint, the hierarchy of the data acquisition system (see Fig. 3) can generalize the information infrastructure within a

Table 3
Significant works related to data-driven modelling and analysis.

Work	Year	Contribution
Giacone [62]	2008	Statistical process control approaches were used as a modeling method for energy management in small and medium-sized companies.
Motlaghi et al. [63]	2008	Used a simple neural network model to model a crude oil distillation column and optimized the process
Errico et al. [64]	2009	Performed modelling of a crude distillation system to achieve energy saving. Utilizes real data from processing plant to construct process model in a commercial process simulator (i.e. Aspen Plus).
Le and Pang [65]	2013	Implemented an energy-saving decision system based on wavelet transformation, segment clustering and support vector machines (SVM).
Katchasuwanmanee et al. [66]	2015	Revealed an energy-smart production management system named "e-ProMan". It uses real-time and historical data to perform correlation analysis on energy, work and data flow on industrial machines.
Ronay and Bhinge [60]	2015	Performed energy prediction for the consumption of a machine tool using an ensemble of neural networks that were optimized by the NSGA-II (Non-dominated Sorting Genetic Algorithm II).
Zhou et al. [67]	2016	Revealed that models for data-driven energy management systems are mainly based on evolutionary optimization, mathematical programming, machine learning techniques and statistics.
Zou et al. [68]	2017	Used a stochastic mathematical model to relate sensor data to state variables and disruption events. Carried out an energy-saving evaluation based on energy-saving opportunity window concept.
Durrani et al. [61]	2018	Data-driven optimization of a crude distillation unit for the consideration of energy efficiency using Taguchi method, Genetic Algorithm and Artificial Neural Networks.
Adenuga et al. [69]	2019	Demonstrated an energy efficiency analysis modelling system which considers aspects of energy consumed, operational energy costs, baseline power, production power and utilized total power.
Ji et al. [57]	2019	Used a Deep Belief Network with a combination of a Genetic Algorithm to reduce energy consumption in a simulated machine tool.

Table 4
Significant works which include industrial implementation of energy-saving solutions.

Work	Year	Contribution
Gao [73]	2013	Google implemented a Neural network-based controller to predict and learn the power usage efficiency of its industrial data centre. The application was successful in catching erroneous meter reading and optimize plant operational parameters.
Touš et al. [71]	2015	Used a combination of Artificial Neural Network and regression analysis to achieve a stochastic Monte Carlo optimal planning decision in a waste-to-energy plant. The work implemented the simulation tool in a combined heat and power (CHP) plant within the Czech Republic and improved planning accuracy by 45%. This relates to 130 Euro increase in daily revenue.
Xu et al. [74]	2017	Developed a novel system architecture focused on distributed energy savings and Big Data analysis for industrial cloud manufacturing. The system was implemented in the form of a functional module.
Zhang et al. [31]	2018	Utilized a complete architecture of energy Big Data perception and acquisition which utilized IoT. Implemented a proof-of-concept application in the ceramic manufacturing industry. The energy monitoring system successfully identified potential energy-saving opportunities from a poorly maintained ball mill unit.
Teng et al. [75]	2019	Proposed the combination of correlation-based principal component analysis-aided statistical process optimization (PASPO) to find optimal processing conditions from the SCADA system which simultaneously improved product quality, process energy and environmental impacts. The framework was deployed in a Malaysian oil refinery where process energy improved by 3.5%, Acidification Potential improved by 90.89% while main product yield and quality improved by 84.4% and 46.5% respectively.
Gallagher et al. [70]	2019	A cloud computing-based system called “IntelliMaV” was applied to verify the energy savings in near real-time. The system uses various machine learning models (such as ordinary least square, k-nearest neighbours, Artificial Neural Network and Support Vector Machines) for learning the data. The system identified various energy-saving potential from a large biomedical manufacturing facility in Limerick, Ireland.

conventional industrial plant. As the basis for information infrastructure, sensors and machines are connected to input/output (I/O) to transfer physical and measured information to electronic input. For most processing system, there exists a programmable logic control (PLC) to deal with process actions which require fast responses. The supervisory control and data acquisition (SCADA) system is a monitoring system for the overview of the manufacturing area. Control set-points and operational settings are mostly carried out at the SCADA level. Manufacturing execution system (MES) are higher-level computerized system to track material and energy flow and to aid with production management. Lastly, enterprise resource planning (ERP) is a system used in management-level for customer services, sales, procurement, production, distribution, accounting, human resource, corporate performance and governance. Conventionally, the data is collected from the bottom of the hierarchy (Fig. 3) and gradually moving up. Processing data is also stored in some cases and processing historian software and databases can be used. For the computation and optimization of system and operation, the data can either be sent to embedded devices, cloud services or a centralized machine to be processed. Alternatively, the decision made by the computation will flow in the reverse direction of the hierarchy, ultimately being implemented on the machine level.

In large industries, the *de facto* standard of data acquisition system is the SCADA system with Modbus RTU protocol [78]. However, in small-and-medium enterprises, Máša et al. [28] discussed that many facilities have incomplete data acquisition system and the implementation of SCADA systems (at the very least) is crucial for energy-saving projects. Yuan et al. [79] also observed the incompleteness of energy Big Data in the industry due to non-ideal data collection infrastructure. Additionally, Yan et al. [19] discussed that industrial information is multisource, heterogeneous and sometimes unstructured. The existence of good information infrastructure is crucial for energy-saving projects. Nevertheless, the implementation of SCADA system in existing industrial facilities is a major challenge due to the expensive costs of the systems. For example, Stojkovic and Vujosevic [80] demonstrated that even a compact and small experimental SCADA system would cost around 10,000 USD in Europe. OmniSite company [81] estimated that a typical industrial SCADA system (20 stations) in the United States would cost a total of 476,500 USD in 10 years. In many cases, the integrity of SCADA system should not be compromised for costs, as disastrous incidents can occur due to inadequate security within the system. Works of Miller et al. [82] showed that poor implementation or operation of SCADA systems can potentially give catastrophic accidents due to malware infiltration and misuse of resources. Furthermore, for industrial processes, the SCADA system should not fail under power shortage. The cost of mitigating power shortage is often overlooked. For instance, a single industrial-grade 10 kVA uninterruptable power supply (UPS) system that can acts as backup power for 18 min could easily cost more than 3500 Euros (approximately 3855 USD) [83]. Zhu [84] even pointed-out that data acquisition for intelligent analysis is a compromise between the cost for information infrastructure and the data quality. The work highlighted the need to process corrupted data under cost-constraints. Evidently, industrial data acquisition is not a simple task.

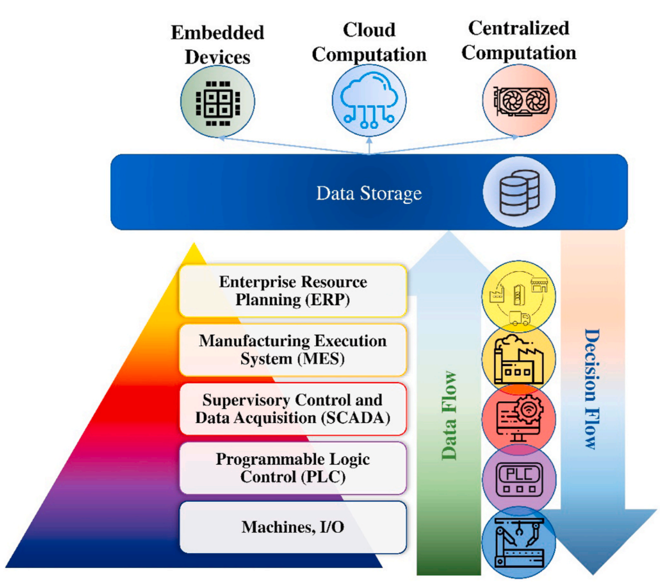

Fig. 3. Typical hierarchy of data acquisition systems.

3.1. Industrial internet of things for data coverage

A recent direction to reduce the cost of acquiring industrial data is by implementing the industrial internet of things (IIoT) sensors and infrastructures [76]. In terms of device pricing, Zheng et al. [85] pointed out that IoT improves intelligent interconnection of data infrastructure by utilizing low-cost information gathering and dissemination devices. As the cost for IoT devices diminishes with technical progress, many processes can benefit from an increased awareness of data-driven analytics [86]. Works of Xiaojun et al. [87] estimated that IoT system can reduce hardware costs by 1/10 for the purpose of industrial monitoring and forecasting. Moreover, the amount and variety of data that is enabled by industrial IoT infrastructure are remarkable. Ahmed et al. [88] discussed that technologies from IoT have enabled explosive growth in the number of devices connected to the data infrastructure, allowing for Big Data analytics. The work discussed that IoT environment provides opportunities for intelligent decision-making, improved efficiencies, reduction of data silos and value-added applications. Additionally, Shrouf et al. [77] also repositioned the importance of IoT in smart factories, highlighting that IoT can improve the factory sustainability, mass customization, flexibility, planning methods, proactive maintenance, connected supply chain and energy management. The perspective that industrial Big Data can be achieved as a result of IoT adaptation in manufacturing had also been proposed by Mourtzis et al. [89]. Evidently, the implementation of IoT in Industry 4.0 would greatly improve data collection frequency, data coverage and data variety.

The pathway towards industrial IoT is not all sunshine and rainbows as there are many major challenges. Kim et al. [90] surveyed that IoT for energy management faces challenges from a technological prospect, market potential and regulatory environment. One of the most significant technical challenges is the robustness and reliability of industrial IoT [91]. Specifically, Duan et al. [92] even discussed that the reliability of data transmission has become the major bottleneck of the IoT application in industry as data transmission failures can lead to production errors. One of the most recognized solutions for this reliability problem in industrial IoT is by applying 5G-enabled IoT (5G-IoT) technologies [93]. 5G is the fifth generation of mobile, cellular technologies and solution which features over 10 Gb/s of data rate and lesser than 1 ms of latency. Cheng et al. [94] discussed that 5G would enable remote real-time monitoring, operation control and unmanned factory with its low packet loss rate ($<1 \times 10^{-12}$), which the latest 4G transmission technology cannot achieve. The timing of when will 5G be industrially matured and applicable is also to be questioned. Although some researchers expect 5G to be rolling out between 2018 and 2020 [95], with the recent global technological trade war revolving around 5G [96], a delay in rollout is imminent [97]. A conservative expected roll-out date for the 5G technology will be around 2025 [98]. We propose an expected timeline for the evolution of industrial data-driven energy-saving timeline in Fig. 4.

Another significant challenge for the transition of IoT is on the security of the IoT network, software and hardware. By rediscovering past experiences, researchers such as Sadeghi et al. [99] pointed out the challenge in terms of network security for industrial IoT. They revealed that common security attacks on industrial IoT System can be in the form of runtime-attacks, reverse engineering, malware, network eavesdropping, man-in-the-middle attack, denial of service attack, social engineering and phishing. Within these security issues, Sajid et al. [100] revealed that malware and malicious codes are statistically the most pressing security issue for IIoT system. Nevertheless, more research effort is being carried out in the fields of security technologies for IIoT [101] such as ARM TrustZone and variants of security controller. In terms of network and software security, researchers are also working to design trusted execution environments (TEEs) for industrial IoT applications [102].

An obvious obstacle for the implementation of IoT devices in the industrial setting is on the standardization of the system to meet industrial regulations [12,90]. For most matured industrial processes, the IoT (and non-IoT) devices have to be up to International Electrotechnical Commission's (LEC) protection rating of IP69k [103] (i.e., dust-tight and able to sustain high-pressure cleaning or steam jet). Furthermore, in specialized industries, more difficult-to-achieve protection standards may apply. For example, in the oil and gas industry, there may be a regulatory requirement for devices to be explosion-proof [104], which can greatly incur costs of industrial IoT implementation. At this stage of development, IoT devices are far from being matured in terms of being standardized for industrial requirements [12]. More researches and manufacturing efforts must be carried out to advance the field.

3.2. Digital twins and cyber-physical systems

The first concept of a digital twin was presented by Grieves [105] to better understand production and design using a virtual factory replication (see Fig. 5). Later, the famous work from Glaessgen and Stargel [106] proposed a digital twin paradigm for NASA and US air force application. The work described digital twin as an integrated multi-physics, multiscale, probabilistic simulation of an as-built system that corresponds to the best available model, sensor updates, system history, etc. Subsequently, Grieves and Vickers [107] extended the original digital twin concept towards mitigating undesirable and critical behaviours in complex systems. This crucial work also discussed the application of digital twins within product lifecycles. A concise guideline for digital twin-driven product design was also presented by Tao et al. [108]. Their work discussed that six important steps were required to build a functional digital twin, which includes (i) build a virtual representation of physical product using CAD or 3D modelling (ii)

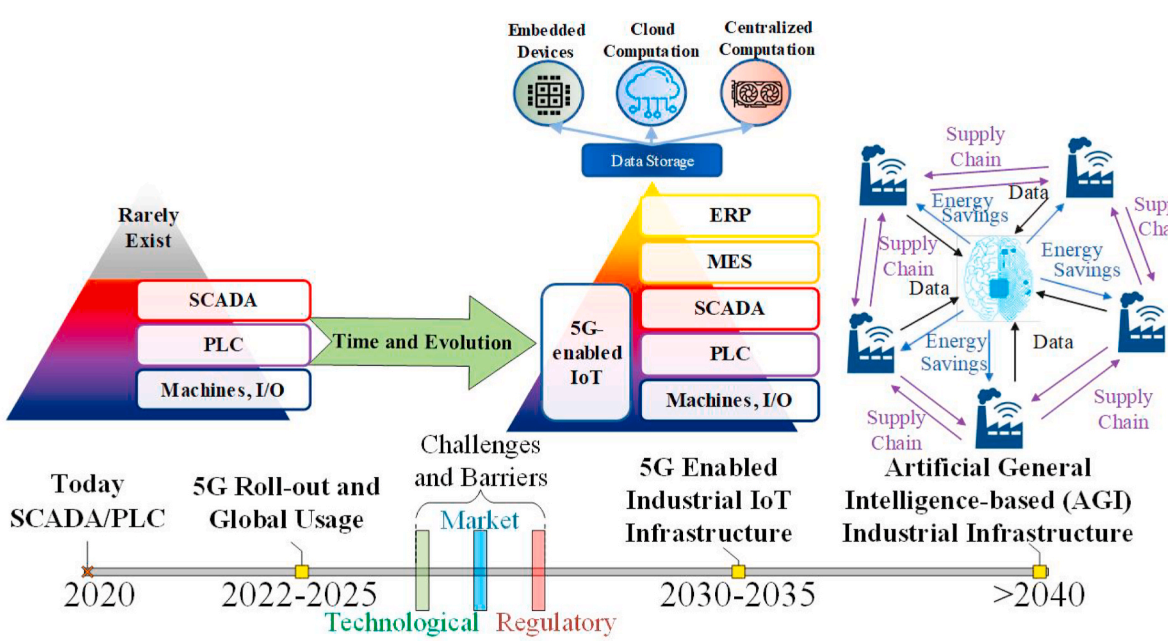

Fig. 4. Expected timeline for the evolution of data-driven energy savings in Industry 4.0.

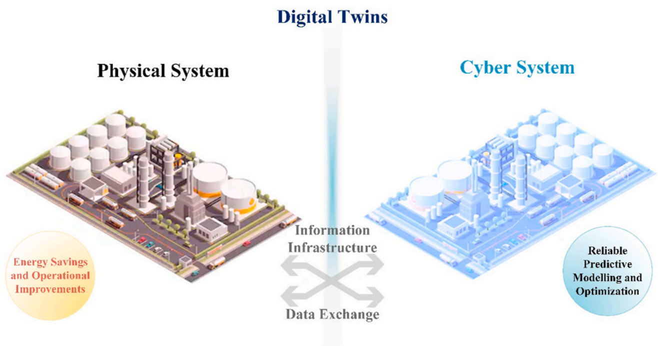

Fig. 5. Illustration of a digital twin for a cyber-physical production system.

process data to facilitate design decision-making (iii) simulation of physical systems in the virtual environments (iv) test the physical system to calibrate the virtual world (v) establish real-time bi-directional secure connections between physical and cyber system (vi) collect more related data for continuous system integration.

Nevertheless, implementing digital twins within existing infrastructures is not an easy task. Uhlemann et al. [109] discussed that challenges related to digital twins include difficulties in real-time data acquisition, requirements for information systems and infrastructure, improper implementation, standardization of data acquisition systems, costs of investment, weak integrity between the cyber and physical world and data security. Furthermore, the paper also highlighted the functional dilemma of the simulation aspect and optimization aspect within digital twins. It is to be questioned whether the accuracy of simulation or optimization should be prioritized. Moreover, it is required to consider and balance between fault-estimation [110] and state-estimation [111] for dynamic systems of digital twins or cyber-physical systems. State- and fault-estimation possess computational dilemma, but can be utilized for effective condition monitoring [112] and predictive maintenance in industrial systems *via* digital twins [113]. Despite the difficulties, the infrastructure of digital twins has been established in various industry-leading companies such as General Electric, PTC, Siemens, Oracle, ANSYS, Dassault, SAP and Altair [114]. Digital twins have also been implemented for the recovery, recycle and remanufacture of waste electrical and electronic equipment [115]. Wang et al. [116] had also shown that digital twins are effective for the application of rotary equipment in manufacturing. Some preliminary software solution for the deployment of digital twins are already available in the market (see Table 5).

The driving model of digital twins was initially based-on 3D finite element analysis (FEA) or computational fluid dynamics (CFD) [106]. However, the time taken to simulate a few minutes of such analysis in the virtual world would take time in the scale of hours in the real world [123] due to the complexity of solving large amounts of particles within the model. In such cases, the simulation cannot provide real-time solutions for the digital twin's requirement. Although leading researchers are able to use finite element-based simulation as the digital twin for smaller cyber-physical systems [124], extending such approach to a full production or manufacturing system is generally difficult without clever simplifications. Due to this difficulty during simulation, some researcher classifies larger manufacturing systems as cyber-physical production systems (CPPS) to specifically address its problems and solutions.

A successful approach to tackle this problem was from using knowledge-based domains. For example, Miller et al. [125] extended their 3D-CAD (Computer-Aided Design) digital twin with behavioural information. By taking in knowledge-based input from experts, they were able to improve the value of their digital twin for utilization. The knowledge-based domain also includes the utilization of data from experiments. Kraft et al. [126] demonstrated that digital twins can benefit greatly from the integrative use of computational fluid dynamics and experimental fluid dynamics. Especially for cyber-physical production systems (CPPS), the existence of knowledge-based data cannot be exempted as there are many human decisions apart from pure physics. For the case of Liu et al. [127], they used knowledge of discrete events, system dynamics and physical components to construct their digital twin for the application of shop-flow manufacturing systems.

Artificial Intelligence (AI) is a more advanced approach to implement seamless digital twins. For instance, C2PS was a digital twin architecture developed by Alam et al. [128] to analyze key properties of cloud-based digital twin such as computation, control and communication. The work utilized a Bayesian belief network which dynamically considers the digital twin's context. Recent work from Luo et al. [129] utilized an artificial neural network to model and utilize the data streams from the digital twin of a CNC milling machine tool. The work proved that AI approach can be used as a multi-domain unified modelling method for establishing a digital twin. Some more advanced works can be found from pioneering teams of AI. Peng et al. [130] from OpenAI demonstrated that a randomized initialization for Deep Reinforcement Learning acts as a method to reduce the "reality gap" to Sim-to-Real problems. Rusu et al. [131] from DeepMind, also demonstrated that for a Sim-to-Real problem, the utilization of a progressive network to bridge the reality gap and policy transfer can perform more efficiently than Deep Reinforcement Learning. It is clear that this is still a progressing field and there are still many developments awaiting.

Table 5
Software solutions for digital twins available commercially.

Software Solution	Company	Features[a]
PREDIX [117]	General Electric (GE)	Supports infrastructure with asset-centric communication, edge-to-cloud, distributed architecture, data management, integrated analytics and embedded cybersecurity. The digital twin is mainly dependant on asset models and knowledge base. Machine learning is also supported in the platform.
IoT Production Monitoring [118]	Oracle	Supports real-time Key Performance Indicators-based (KPIs) analytics. A feature named 'Deep Dive' is available to gain operational visibility in multiple manufacturing levels. Able to diagnose production anomaly, act on prescriptive analytics and reduce inefficiencies.
Akselos [119]	Akselos	Provides a high-fidelity multi-physics 3D-based digital twins framework that utilizes RB-FEA (reduced basis finite element analysis) technology. The technology uses a parametric component approach to pre-solve simulation building blocks to speed up the 3D digital twin. It also supports cloud computation and sensor integration.
Digital Twin Builder [120]	ScaleOut Software	A fully customized digital twin that is constructed by Java or C# object-oriented programming codes. Supports cloud computation and data source integration. Good infrastructure for process event messages and real-time feedback.
Elements for IoT [121]	CONTACT Software	Provides an asset state-based digital twin for monitoring and predictive analytics. Supports sensor integration, 3D models, maintenance history, customer records, cloud computation and edge connectivity.
Seebo Industry 4.0 Platform [122]	Seebo Interactive	Specializes in process flow-based digital twins. The application focuses on process-based predictive analysis, automatic root cause analysis and predictive simulations. Artificial intelligence-enabled analytics and streamline IoT data integration are enabled through Microsoft Azure technology stack in the back end.

[a] As of the time of writing.

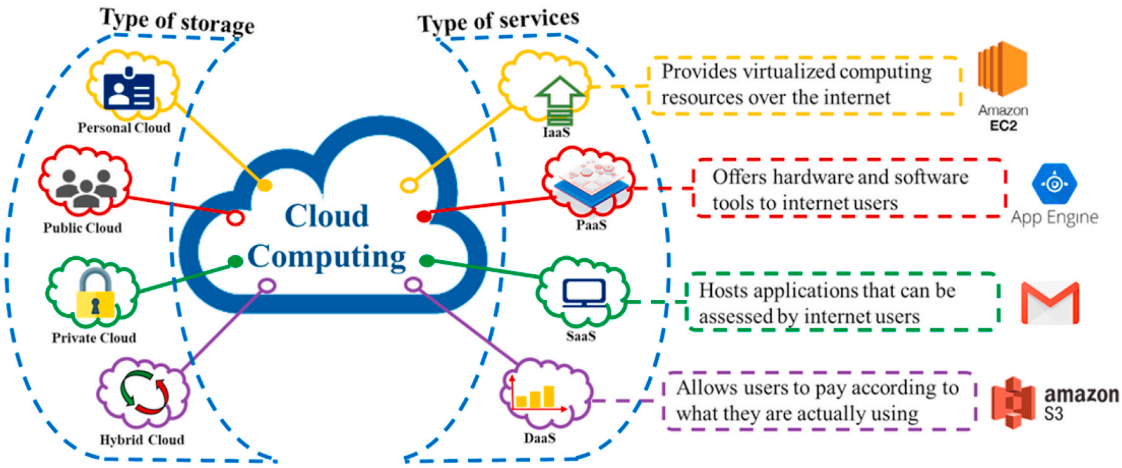

Fig. 6. A holistic view of cloud computing options for industrial applications.

3.3. Cloud infrastructures

Cloud infrastructure is a remote system that covers both hardware and software that support web frontend applications which are connected to the cloud storage [132]. It is the core foundation for cloud computing (see Fig. 6). The application of cloud computing can be back-dated to the early 1960s, where it was introduced as the "intergalactic computer network" by Joseph Carl Robnett Licklider [133]. Nowadays, its utility has been widely extended (e.g., Elastic Compute Cloud by Amazon [134], App Engine by Google [135], etc.). Generally, the cloud services can be distinguished into Infrastructure as a Service (IaaS), Platform as a Service (PaaS), Software as a Service (SaaS) and Data as a Service (DaaS) [136].

The global market for private cloud service is anticipated to reach $ 262.4 billion by 2027 [137]. The ever-expanding market is probably due to the unique advantages offered by cloud computing technology. In terms of the economic aspect, the deployment of cloud computing can avoid the need for high investment cost for constructing a data centre [138,139]. Data security is another factor that caused a high adoption rate of this technology. With the aid of cloud infrastructure, data loss can be avoided. Up till 2018, about 94% of organizations in Europe, the Middle East and Africa (EMEA) have integrated cloud services into their business model [140]. Scalability (or flexibility) is another key feature of cloud computing which allows users to conveniently scale up or scale down the resources (e.g., the need of cloud storage) based on the actual requirement [139]. Aside from that, the high mobility of the cloud service (i.e., the service and data can be accessed anytime anywhere) allows a timely response to be taken. This is important for energy providers especially when the energy sector is getting more and more competitive [141]. Last but not least, the implementation of cloud computing helps to enhance business capability. With the aid of the Big Data analytics which is embedded in most cloud infrastructure, insightful findings can be yielded from the massive data [141]. For instance, by integrating the smart metering with cloud technology, energy suppliers are granted with a bird-eye's view on the electricity flows, starting from the origin to the destination [142]. In other words, outages can be efficiently and accurately identified, while correction actions can, therefore, be carried out earlier.

It is estimated that the annual generation of data for a plant is about 72 TB per year (attributed to the application of IoT) [89]. Therefore, it is vital to have enough data storage capacity to store the tremendous amount of data. Cloud storage is a cost-effective alternative to conventional hardware storage. Based on Fig. 6, cloud storage can be classified into four types, i.e., personal cloud, public cloud, private cloud and hybrid cloud, where some details of these cloud storages are tabulated in Table 6. The deployment of cloud storage in the energy sector have been elucidated in numerous works. For instance, Chen et al. [143] highlighted various roles of open innovation intermediaries (OIIs) (includes providing cloud storage to store and protect the clients' data), in promoting the smart grid industry in China. It can be used to store weather information, energy profile and other data that were generated in the smart grid [144]. Alonso [145] proposed to use cloud storage that was developed by Ingenia to store Big Data that were generated from the energy adapters in an integrated network. Despite the importance of having cloud storage, the huge energy consumption issue for data storage remains a major concern nowadays. It is anticipated that the use

Table 6
Four types of cloud storage available.

Cloud Storage	Description	Example and Pricing
Personal	• Stores individual's data in the cloud environment which is accessible from anywhere at any time. • Syncs and shares data across multiple devices [149] • A subset of public cloud storage	• iCloud (free tier: 5 GB; 50 GB plan: $ 0.0198/GB; 200 GB plan: $ 0.01495/GB; 1 TB plan: $0.00999/GB [150]) • Google Drive (free tier: 15 GB; 100 GB plan: $ 0.0199/GB; 1 TB plan: $ 0.00999/GB; 10 TB plan: $ 0.00999/GB [151])
Public	• Enterprise stores data in an external cloud storage provider, which results in lower data storage cost required. • Lesser flexibility to alter the cloud environment.	• IBM Cloud (below 500 TB: $ 0.022/GB; more than 500 TB: $ 0.020/GB [152]) • Amazon Elastic Compute Cloud (free tier: 5 GB; first 50 TB: $ 0.023/GB; subsequent 450 TB: $ 0.022/GB; over 500 TB: 0.021/GB [153])
Private	• Enterprise stores data in an internal data center, which results in higher capital investment cost and maintenance cost needed. • Provide higher level of security as the enterprise owns the cloud environment.	• Phoenix co-lo (capital investment for a scenario of 100 virtual server instances: >$ 300 k [154]) • Private cloud will become more economically preferable when the monthly spend is more than $ 17 k [155].
Hybrid	• Combines the use of public and private cloud storages. • Critical and confidential data are stored in an internal data center, while other data are stored in an external cloud storage provider.	• Cantemo Portal case (Monthly cost for scenario when 100% of the 2000 TB data are stored in private cloud: $ 24,000–40,000; Monthly cost for scenario when 20% of the 2000 TB data are stored in private cloud and the remaining are stored in public storage: $ 12,800–48,000 [156]).

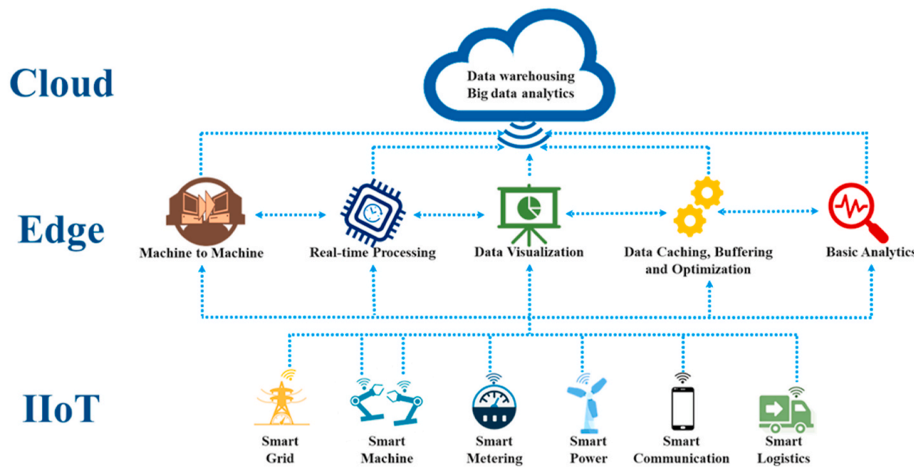

Fig. 7. Linkage between cloud, edge and Industrial Internet of Things (IIoT).

of cloud infrastructure will consume up to 20% of the global power consumption by 2025 [146]. To address this issue, some researchers (e.g., Long et al. [147]and Yang [148]) are exploring ways to improve the energy efficiency of the cloud system.

Aside from selecting the data storage system, an efficient computing system is needed to deal with the enormous amount of data sets. Apache Hadoop [157] and Apache Spark [158] are the two iconic computing systems that can be used to process large-scale data, where the latter offers in-memory cluster computing feature that causes it to be outperforming the other [159]. It is capable to run the same task 100 times and 10 times faster in memory and on disk respectively [160]. In addition, unlike Apache Hadoop, Apache Spark is suitable for real-time and streaming data analysis [161]. Apache Spark can be built on Java, Scala, Python, etc. Till-date, some works have reported the use of Apache Spark in the energy sector. Apache Spark machine learning tool (MLib) is utilized to perform Big Data analytics for well and reservoir management system [162]. More recently, Krome and Sander [163] had developed a hybrid computing system that integrates the use of Apache Spark and the R language, to perform time series analysis for energy price and load profiles forecasting.

Aside from cloud computing, edge computing which the data is processed at the source point rather than in a centralized cloud-based data centre, is being introduced. This computing technology is often used to deal with the time-sensitive data generated from the Industrial Internet of Things (IIoT), i.e. interconnected sensors, instruments, smart devices and facilities (Fig. 7). To achieve the edge computing services, the uses of microcontroller (e.g., Arduino [164], which serves as a simple computer that can run a single program repetitively) and general-purpose computer (e.g., Raspberry Pi [165] and NVIDIA Jetson Nano [166] which is capable to run multiple complex programs; where the latter offers greater capability in machine learning and AI applications) are needed. Note that the edge computing technology can be implemented in the energy sector to enhance production capability and improve process efficiency. For example, in a scenario where the windmills are located at remote areas which is not accessible to the internet, edge technology can be implemented to (i) collect and analyze data; and (ii) optimize and make decisions (e.g., adjust the opening angle of wind turbine blades) [167]. In one of the recent publications, an Edge-IoT platform was proposed to effectively reduce the energy consumption of an energy distribution network [168].

To efficiently process the massive amount of data, specialized hardware such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs) are required [169]. In general, GPUs and TPUs are used as accelerators for the sub-portions of the model that can be decomposed into data-parallel computations [170], where the latter is designed specifically for neural network machine learning. The overall comparisons of each type of processing unit are highlighted in Table 7.

Table 7
Comparisons between the three processing units [171–173].

Criteria	CPU[a]	GPU	TPU
Compute primitive	Scalar (1 × 1 data unit)	Vector (1 x N data unit)	Tensor (N x N data unit)
Application	General-purpose	Graphics Rendering	Machine Learning model
Operations per cycle	tens	tens of thousands	up to 128 thousand
Relative Performance to watt ratio (based on CPU)	1	2.9	83
Throughput per second[b]	5482	13,194	225,000
Training cost[c]	$ 1.0507	$ 0.3995	$ 0.2410
Machine cost	$ 0.14/hour	$ 1.87/hour	$ 4.57/hour
Developers	Intel, NVIDIA, IBM, Samsung, etc.	NVIDIA, AWS[d], AMD, PowerVR, etc.	Google

Footnote.
[a] Central Processing Unit.
[b] Under 7 ms latency limit.
[c] Trained with Adam until 0.25 validation loss was reached for 5 runs.
[d] Amazon Web Services.

3.4. Potential for blockchain

The blockchain technology was originally designed by Satoshi Nakamoto to serve as the main foundation for Bitcoin [174]. In general, it is a growing list of records (or blocks) that stored the information of all committed transactions [175]. As shown in Fig. 8, The blockchain architecture can be decomposed into six layers, i.e., data layer, network layer, consensus layer, incentive layer, contract layer and application layer [176]. This unique structure enables the automated execution of smart contracts in the peer-to-peer network which allows multiple users to make changes in the ledger simultaneously [175]. This technology enables four key features of persistency, anonymity, decentralization and auditability which further improve the overall cost-effectiveness and the efficiency of a data management system [177].

To date (as of 2019), three generations of blockchains have been developed (see Fig. 9). *Blockchain 1.0* refers to the origin utility of blockchain technology which generally used for trading cryptocurrencies [178]. Bitcoin [174] system is one of the most well-recognized examples that utilized blockchain technology to allow peer-to-peer transactions that operate without the need for a centralized administrator [179]. This first generation of blockchain is then evolved to

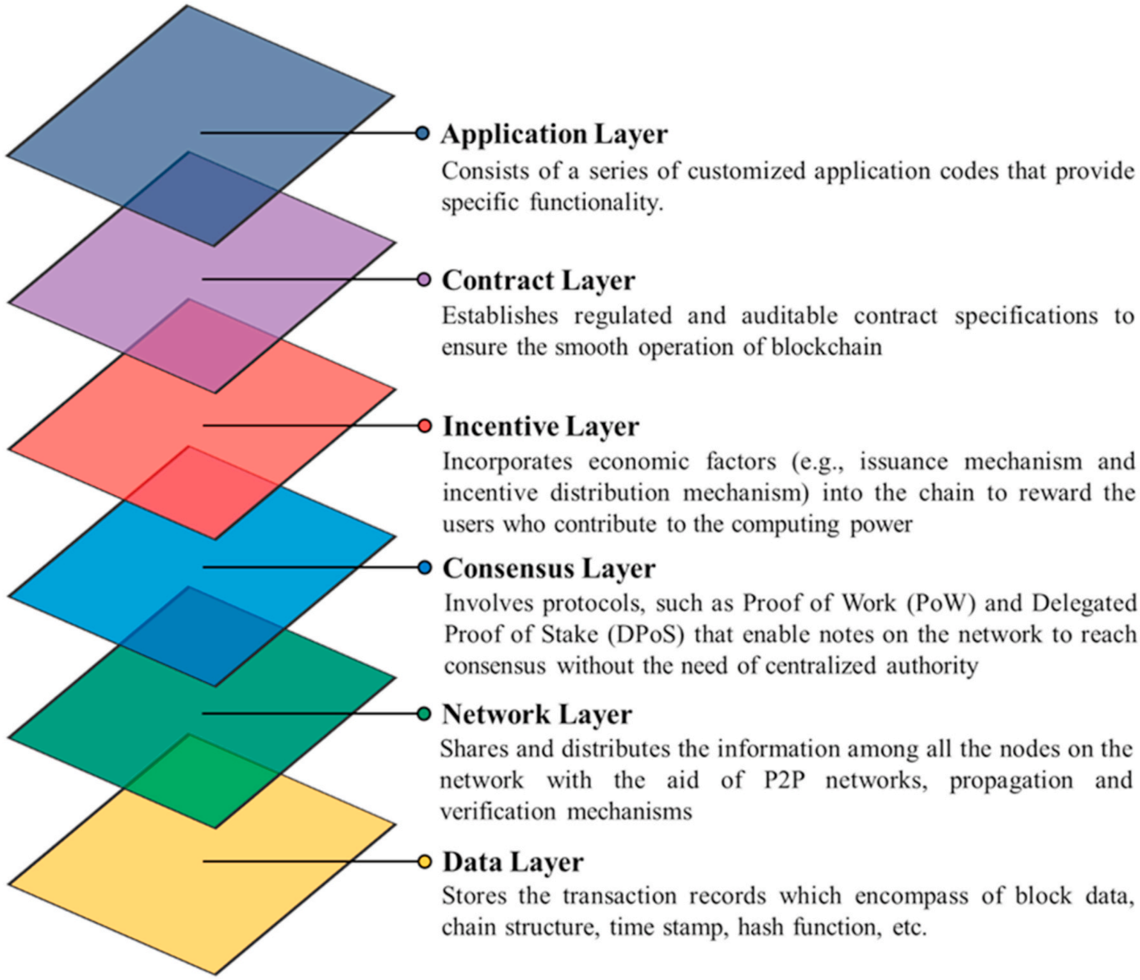

Fig. 8. Generic blockchain architecture.

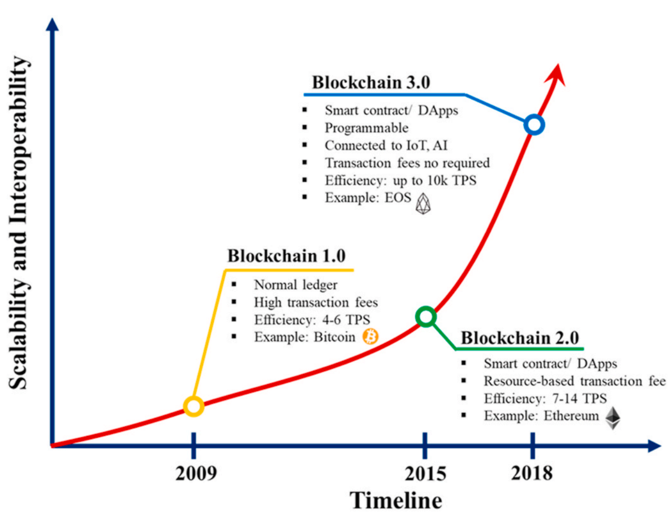

Fig. 9. Evolution of blockchain technology.

Blockchain 2.0, where the values being transferred is no longer restricted to currency but in the form of smart contracts (i.e., programs or scripts that will self-operate after certain conditions and requirements are met without the need of manual commands) [180]. This generation of blockchain focuses on the deployment of decentralized applications (dApps). There are three well-recognized features for dApps, i.e., (i) open-sourced (changes are based on the consensus of the users and developer where the code base is available and accessible for scrutiny), decentralized (all data are stored on decentralized platform to encourage transparency, trust and efficiency) and incentivized (rewarding system to encourage the involvement of the validators). Ethereum, which was proposed by Vitalik Buterin [181] in late 2013, is one of the most prominent examples for *Blockchain 2.0* applications. Unlike the Bitcoin system, Ethereum focuses on executing codes for any decentralized applications that are deployed in the network, instead of merely offering a peer-to-peer cryptocurrency transaction system. Under this context, Ether is the cryptocurrency that fuelled the blockchain, where it is paid to run the smart contract. Blockchain technology is currently applied in diverse applications (also known *Blockchain 3.0*) such as IoT [182], healthcare system [183], education [184], digital government services [185], etc.

In other words, the functionalities of blockchain technology are no longer limited to the finance and asset transfer-related applications, and therefore, higher scalability is obtained [186]. There are numerous successful blockchain-based decentralized operating systems under the third generation of blockchain which non-exhaustively includes EOS [187], Cardano [188] and ICON [189]. More recently, major companies such as IBM, Intel and Microsoft, are attempting to incorporate AI and machine learning into the blockchain system [190]. The unique ability of AI and machine learning which is capable to address and express uncertainty opens another possibility for blockchain application in solving complex problems [179]. Under this generation, a novel data structure, Tangle (i.e., one of the distributed ledgers that is based on

Directed Acyclic Graph (DAG)) is commonly being implemented as it can overcome the efficient issues of the conventional blockchain network [191]. IOTA ledger is one of the notable DAG-based ledgers that was designed to track, record and execute decisions between machines and smart devices that are connected in the IoT network [192]. It was founded by David Sønstebø and his colleagues back in 2015 [193]. Fig. 10 represents the schematic diagrams for the structures of conventional blockchain and tangle. As shown, unlike the conventional blockchain structure, the data flow in a tangle is constrained to a single direction [194]. This enables higher efficiency of data transfer, i.e., about 100–270 times faster than that of the conventional blockchain technology [194]. As a trade-off to this increment in terms of efficiency, tangle provides a lower level of security due to its less robust nature of the structure (i.e., each device merely needs to validate two previous transactions).

Till date, blockchain technologies have been gradually applied in the energy sector to fulfil a diverse range of objectives, including (i) bill payment with cryptocurrency; (ii) rewarding system using cryptocurrency; (iii) peer-to-peer energy trading market; (iv) imbalance settlement for energy market; (v) blockchain-enabled IoT platform; (vi) blockchain-enhanced smart metering; (vii) certification system; (viii) electric vehicle application; (ix) blockchain-based Life Cycle Assessment (LCA); (x) AI-enhanced blockchain for market forecasting; and (xi) blockchain-enhanced Intelligent Energy Storage (IES). These applications are then classified based on the corresponding blockchain technology used, while the remarks of each application are summarized in Table 8.

Despite the vast potential of blockchain technology, there are still various challenges that need to be addressed. For instance, the deployment of distributed ledger technology (DLT) solutions (e.g., integrating smart meters with blockchain network) can be costly [195]. Aside from this, the low throughput (i.e., the transactions which can be cleared per second) of the technology is another main concern that must be overcome. For instance, the conventional electronic payments that utilized a centralized network can clear thousands of transactions per second (e.g., Visa can support about 1700 transactions per second [196]), whereas Bitcoin network which utilized distributed network can merely address about 7 transactions per second [197,198]. Finally, privacy concern is another key challenge that may hinder users from venturing into blockchain-based interventions. Despite the economic benefits attributed from the blockchain-enabled IoT platform, users might still be reluctant to share their personal information (e.g., consumer behaviour) into the open-source network [199]. For this reason, numerous works have explored strategies for the development of privacy-friendly blockchain-based platform [200–202].

4. Policies and government initiatives

Energy efficiency is continually improving according to yearly evaluations. Industrial energy consumption in 2013 was 17% below its 2000 level and represented 25% of the energy used by final consumers. The chemical industry was the main consumer with 19% of the total industrial consumption, followed by steel with 18% in 2013 [235]. The study [236] focuses on the evaluation of energy use in most demanding industrial sectors (iron and steel, chemical and pharmaceutical, petroleum refineries, pulp and paper, etc.). It presents that process heating was the most significant energy use (about 66% of total energy consumption) followed by electricity use (26% of total energy consumption) in 2013.

Policymakers whose motivation is mainly decreasing energy consumption, try to introduce various rules and incentives. One of the tools applied is energy auditing. In the case of EU, this is specified in the energy efficiency directive 2012/27/EU [21]. Regular energy audits are mandatory for large enterprises and it is recommended to introduce programs encouraging SMEs to undergo energy audits too. The directive also emphasizes the necessity for high-quality audits which should be carried out by accredited experts or supervised by independent authorities in a cost-effective manner. Energy audits should also respect regional or international standards such as EN ISO 50001 on energy management. Some of the government initiatives from various countries are tabulated in Table 9.

The common method of energy efficiency assessment for action plans and regulations in various countries revolves around energy audits. The audits usually propose implementation of an energy management system which should be responsible for all the measures and other future activities (monitoring of energy consumption, evaluation, maintenance, etc.). Often, a large part of the energy audit is focused on improving buildings efficiency by use of insulating building elements, energy-efficient lights, energy-efficient air conditioning, rarely efficient HVAC setpoints and scheduling, etc. Regarding the energy-saving measures for the process itself, the audits typically recommend replacing the low-efficiency units with new highly efficient ones, use of adjustable speed drivers, occasionally process integration or waste heat recovery. Some tips and guidelines can be found, for example, in these documents: Worrell et al. [248], Hesselbach et al. [249] and ICF Consulting Ltd [236]. However, implementation of these energy-saving measures often

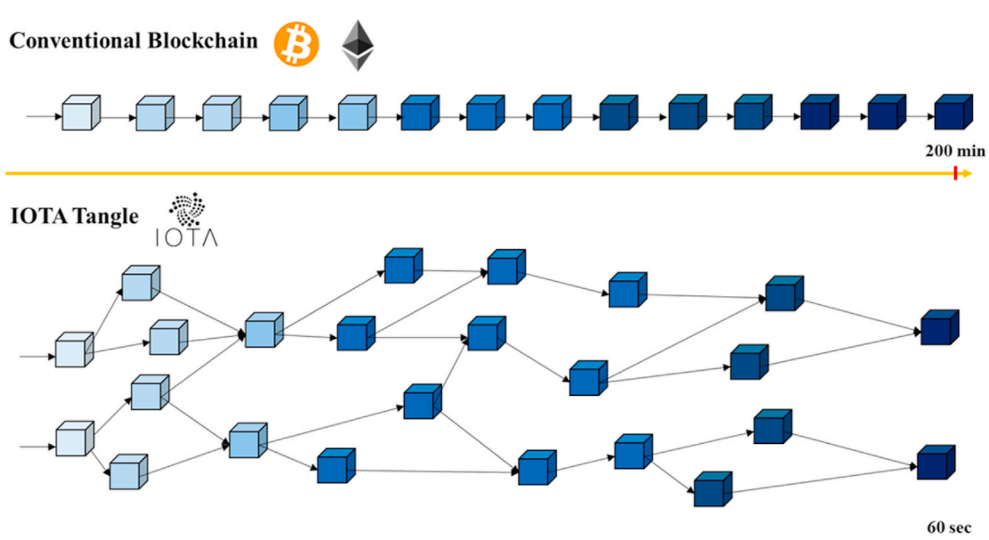

Fig. 10. Schematic diagrams for the structures of conventional blockchain and tangle (DAG-based blockchain).

Table 8
Energy saving-related application of each generation of blockchain generation.

Blockchain Technology	Application	Remark
Blockchain 1.0	Bill payment with cryptocurrency	Recently, more utility offering companies accept bill payments with cryptocurrencies, e.g., Eva Energy [203] in Romania, NexGen Energy [204] in New Zealand, Elegant [205] and Enercity AG [206] in Germany. Despite the analysis shows that the use of Bitcoin can benefit consumers from 4 to 6% reduction in their electricity bill [207], most users are still using fiat currencies to complete the transactions instead.
	Rewarding system using cryptocurrency	KWATT was used to reward energy supplier that had committed into waste-to-energy initiatives (i.e., 1 coin is awarded for every kW of energy generated from waste) [208]. Whereas SolarChange had launched SolarCoin, a cryptocurrency which is designed to reward energy supplier that generate and supply solar energy [209]. On the other hand, customers who showed good behaviour, such as supporting carbon-neutral energy can also be incentivized with such virtual currency (e.g., GoodCoin [210]). All the aforementioned tokens or coins can be used to mine other available virtual currencies or be sold to reclaim fiat currency [198].
Blockchain 2.0	Peer-to-peer energy trading market	Peer-to-peer energy trading market is an interconnected network that allows users to trade energy, i.e., users that have excess energy can either store or sell to other users who encounter energy deficit [211]. To date, few companies, including The Brooklyn Microgrid in the United States [212], Power Ledger in Australia [213], WePower [214] have contributed to the development of such trading ecosystem (some noted as microgrid system). Mihaylov et al. [215] on the other hand, had proposed the use of virtual currency (i.e. NRGcoins) to represent the energy flow into and from the grid, where the rate of the NRGcoins varies according to the real-time supply demand situations.
	Imbalance settlement for energy market	Smart contract in blockchain technology enables the near-real-time tracking and confirmation of the billing [198,216]. With the aid of the distributed ledger technologies, the issue of having a huge settlement period (up to 28 months [198]) can, therefore, be resolved.
Blockchain 3.0	Blockchain-enabled IoT platform	Blockchain can be utilized to facilitate the data exchanges between IoT devices [198], where the interoperability of the IoT platform can be assured [217]. Under such platform, smart devices can be programmed to achieve certain desired goals, such as minimizing the need for external energy. Therefore, users can now make more rational decisions about their respective energy usage (e.g., the Swedish housing society case study proposed by Mattila et al. [218]). Grid+ [219] is one of the blockchain-based energy companies that connect consumers to the grid *via* the integration of blockchain technology with IoT devices. This can further result in an energy bill reduction of about 40% [220].
	Blockchain-enhanced smart metering	Due to the nature of blockchain that could offer higher traceability, the utility charges can become more transparent [198]. Companies are exploring applications of blockchain technologies for various metering systems, such as electricity (e.g., Klenergy Metron developed by Pylon Network [221], blockchain-based pay-as-you-go solar services offered by M-PAYG [222]), water (e.g., automated system that can make decisions on maintenance scheduling by Engie [223]) and heat (e.g., the four Energy Innovation Projects launched by Blocklab [224].
	Renewable energy certification (REC) systems	Conventionally, power is non-traceable as it will be mixed with others in the common pool [225]. To address this issue, companies such as Acciona [226] and SP group [227] have adopted blockchain technology so that their clients can verify that the energies they consumed were sustainable. As a side note, smart contracts are used to perform automated tracking of REC [198].
	Electric vehicle application	The use of blockchain technology offers electric vehicle users greater rights in selecting the source of power supply and provides greater transparency in the power charges (e.g., Share&Charge [228]).
	Blockchain-based Life Cycle Assessment (LCA)	The blockchain-based LCA enables a more reliable and trusted data collection correspond to the actual energy consumption throughout the entire product life cycle [229]. In a recent publication, Lu et al. [230] had highlighted the potential of blockchain technology in tracking the life cycle performance of the oil and gas supply chain. This intervention is essentially useful for policymaking, product design and improvement, supply chain management, environmental assessment and process debottlenecking.
	Artificial intelligence (AI) enhanced blockchain for market forecasting	Numerous companies aim to develop an AI-enhanced blockchain to achieve accurate and efficient forecasting of the energy production and consumption pattern [231]. The Bittwatt platform [232] and Jouliette platform [233] are few of the notable examples that applied AI and blockchain technologies to conduct a successful market forecast.
	Blockchain-enhanced Intelligent Energy Storage (IES)	Blockchain-enhanced IES integrates the strength of the two technologies (blockchain and AI). Blockchain technology serves as a media to trace the energy information, such as charges, prices and carbon footprint data that can facilitate users in making energy storage management decisions; where AI, on the other hand, is capable to provide optimal energy storage management decision for users, based on collected data [234].

faces many barriers from which the main barrier is the economic barrier as demonstrated in the case of Sweden [250]. Two years' simple payback period (SPP) is mostly considered to be feasible for industrial enterprises. Few of them may consider payback period up to 5 years, while anything with a higher payback period is considered not feasible [236].

ICF Consulting Ltd [236] evaluated over 230 energy-saving opportunities with respect to the payback period. In the category of opportunities with SPP period under 2 years, integrated control systems are supposed to have the greatest energy-saving potential followed by sub-metering and interval metering (it is possible to show more measures) for energy use monitoring. However, there might be other opportunities for process efficiency improvement. These can be uncovered by applying advanced modelling, simulation and optimization methods. Digitalisation in Industry 4.0 provides new options thanks to the availability of large amounts of operational data. Nevertheless, a procedure utilizing data for energy efficiency improvement by advanced methods must be time and cost-effective, so it satisfies the 2 years payback period rule.

5. Traditional and modern industrial implementations

The concept of energy savings was formed in the 1970's, when the energy crisis struck the American domestic oil supply. In 1973, American's support for Israeli in the Arab-Isreali War had triggered the Arab nation to stop supplying oil to the American. With that, the oil price had tripled. This had exposed the American with the risk of the energy crisis. The concern in the energy crisis has created the momentum to increase public awareness on energy conservation [251]. The concept first started with the mentality of "just use less". Delmes et al. [252] highlighted that energy conservation is highly consumer behaviour dependent. The reluctance in conserving energy is mainly due to the lack of information, ease of convenience and lack of immediate result [253]. However, the constant increase in energy demand has led the global community to

Table 9
Initiatives and policies of countries and regions for energy improvements.

Country or Region	Initiatives or Policies	Description
European Union	Revised Energy Efficiency Directive [21,237]	The directive sets the target for an improvement in energy efficiency at EU level of at least 32.5% in 2030, following with an extra 20% target in 2020.
	National Energy and Climate Plant (NECPs) [238]	Energy and climate plans are designed to meet EU's target for 2030. EU Member States are to establish a national energy and climate plant from 2021 to 2030. The plans address issues related to energy efficiency, renewables, emissions reductions, interconnections, research and innovation.
United States	Advanced Manufacturing Office (AMO) Initiatives [22]	Provided more than 1300 industrial partnerships and projects for energy saving and energy efficiency in US. Conducted numerous studies that related to energy utilization.
	Federal Energy Management Program (FEMP) [239]	The program focuses on services to aid agencies in meeting water and energy reduction targets (such as audits, energy management, efficiencies, operations and contracts). Actions from the program are mandated by laws which are included in title 42 of the United States Code.
	State Energy Program and Energy Efficiency and Conservation Block Grant Program [240]	Reward projects (according to American Recovery and Reinvestment Act) that reduces operating costs, develops manufacturing capacity, improve energy performance, produce clean energy, enhances environmental performance or a combination of the above.
	State & Local Energy Efficiency (SEE) Action Network [241]	An action network facilitated by the federal government to help states, utilities and other stakeholders to take energy efficiency to scale and achieve targets by 2020. Provides policy design for energy audits and energy efficiencies.
China	Plan for Energy Development [23]	National Development and Reform Commission (NDRC) and the National Energy Administration (NEA) provided five-year plans to improve energy systems, save energy, promote renewables, target energy efficiencies, develop energy market, strengthen energy cooperation and achieve energy sharing.
	Chinese Laws and Regulations with the Energy Charter Treaty [242]	China adopted "One Belt One Road" imitative and various energy treaty practices. The new Silk Road Economic Belt extends to Asia, Africa, Pacific countries to construct an "Energy Silk Road" for global energy benefits.
	Mandatory minimum efficiency standards [243]	Developed by China National Institute of Standardization to provide mandatory energy efficiency standards to residential and commercial appliances, lighting, heating and cooling equipment.
India	Perform Achieve and Trade Scheme (PAT) [24]	Ministry of Power initiated the scheme to improve industrial energy efficiencies, strengthen energy security, lower emissions, improve renewables and contribute to the country's economic value. The scheme covered various energy-intensive sectors for benchmarking.
	The Energy Conservation Act [244]	The Act empowers the government to notify energy-intensive industries, establish energy standards, appoint energy audits and other regulations regarding energy conservations.
	Energy Efficiency in Small and Medium Enterprises Scheme [245]	Bureau of Energy Efficiency and designated state agencies have initiated diagnostic studies in various enterprises cluster. The task was to conduct energy audits, prepare project reports, enhance capacities of service, provision for financing, improve awareness and outreach.
Malaysia	National Energy Efficiency Action Plan [25]	Ministry of Energy, Green Technology and Water prepared a budget (approximately $ 13 million) to promote low energy prices, finance for energy efficiency, national plans for energy efficiency, champion to drive energy efficiency and consistency in embarking on energy efficiency. The action plan covers energy targets up to the year 2025.
	Economic Transformation Programme [246]	The programme covers a large variety of entry point projects and allocated 14 million MYR (approximately $ 3.3 million) for the improvement of energy efficiency in the energy industry. The action on energy efficiency focuses on better energy-efficiency practices, simulate sales of energy-efficient appliances, provide co-generation economic support and other energy-efficient technologies.
	Green Technology Master Plan [247]	The master plan was established by the Ministry of Energy, Green Technology and Water to focus on six key sectors which include energy, manufacturing, transportation, building, waste and water. The purpose of the master plan is to provide policy directions towards green technology, elevate economics of energy-efficient technologies, improve cost efficiency, lower energy prices and accelerate technological advancement.

extend energy conservation to energy efficiency.

Even though energy generation has contributed up to 72% of the global greenhouse gas (GHG) emission [254], the EIA has projected that the global energy demand will continue to increase between 2018 and 2050 [255]. Borozan [256] also highlighted the importance of energy contributing to the global economy. As such, the global community improves energy consumption by prioritizing energy efficiency instead of energy conservation. With that, Petrecca [257] recommended an energy management strategy of reducing the energy consumption per unit of products with a constant or reduce cost from the operation.

In practice, the conventional approach to energy saving is highly dependent on policy and management approach through energy audits, management commitment and standard operating procedures [35]. Many countries such as Malaysia [258], South Africa [259], United State [260] and European Union [261] have prioritized energy efficiency approach in order to meet the energy demand without compromising the global warming. In the European context, an energy manager training program was implemented in the in early 2000 under the EUREM initiative to increase energy efficiency in companies [262]. Apart from European region, Malaysia also has its energy manager program under the Energy Commission Malaysia. According to Li et al. [263], energy management for building can contribute to 20% energy saving which reflects as 60 billion Euros of saving.

The paradigm shift in industry 4.0 has introduced data analytic with Big Data [67] and machine learning [70] to enhance the energy-saving strategy. Di Orio et al. [264] reviewed that data-driven models such as machine learning techniques can be trained to predict and plan for energy saving. Basl [265] added that the influence of industry 4.0 encourages industries to installation IoT devices to move towards smart factories. With that, many industry players are tapping on to the potential of Big Data to enhance and improve productivity through data analytics. Li et al. [266] had also compared the performance of machine learning models with traditional human estimation. The outcome had proved that the machine learning model is far superior to the human being's ability and capability when dealing with complex energy prediction. The accuracy and prediction from the machine model have outperformed the human's performance extensively. The new era of digitalisation has empowered data-driven technology to provide optimized and cost-effective solutions that the industry can leverage on. The differences between modern and conventional approaches for energy savings can be found in Table 10.

5.1. Barriers and gaps between evolving academics and industry

The era of the information society is transitioning towards a knowledge-based society [274]. Knowledge has become the new

Table 10
Comparison between conventional and modern.

	Conventional Approach	Modern Approach
Data collection method	Human and instrumentation.	IoT-based infrastructure.
Cost	Cost is dependent on human experience, qualification and expertise [267].	High fixed cost due to investment cost, servicing cost and upgrading of parts [268].
Flexibility on task fulfilment	Humans need to be trained to achieve the flexibility to perform multi-tasking task [268]	High flexibility depending on computation algorithm and model [269].
Flexibility on availability	Humans are restricted by mental and physical limitation.	High, as the algorithm can operate on 24 h mode [270].
Capacity on information processing	• Time intensive [271]. • The ability to detect errors and corrections may not be consistent.	• Moderate to high time effectiveness in data processing [272]. • Moderate to high ability in error detection and corrections.
Ability on problem-solving [268]	• Solving ill-structured problems. • Managing exception conditions. • Perform collaboration to troubleshoot heuristics-based problems.	• Learning and formalizing the troubleshooting process. • Able to detect and recommend corrections based on repeated problems. • Perform predictions on standard problems based on continuous monitoring.
Performance variation	Performance variance is high as it is dependent on individual capacity [267].	Performance variance is low.
Quality variations on decision making	Decision making is highly dependent on individual experience, qualification, problem-solving ability and competency [267].	Decision-making performance is highly depending on the quality of the input data. However, the quality can be improved by training the system with larger datasets [273].

economic resource where knowledge transfer is important and necessary in order to commercialize knowledge through proper channels [275]. Bekkers and Bodas Freitas [276] found that about 10% of new products or processes are the contributions from academics. The industry and academic collaboration have formed a critical relationship worldwide [277] especially in today's knowledge-based society [278]. Collaboration between an organisation with different expertise and perspective can be difficult. However, the outcome can be impactful.

Many research outcomes have highlighted the importance of collaboration between industry and academics. For instance, a healthy and strong collaboration can boost innovation performance, enhance product development [279] and improve the novelty of a product [280]. A study has found that collaborative research and informal contacts with the industry were more important than contract research to establish effective knowledge exchange [281]. In collaborative research, both academic and industry can gain mutual benefits, especially on knowledge transfer for innovative ideas. Table 11 lists the benefits that both parties can leverage to achieve greater output.

With regards to the mutual benefits that the academic and industry sector can leverage upon, challenges arise especially in this data-driven era [293] indicated that the information generated from Big Data analytics can improve decision making. With the available technology, advanced technology can analyze Big Data to obtain insight and high-value output that can bring higher value to the energy aspect of an organization. The sustainable of an organization is becoming more dependent on the organization's ability to manage Big Data, knowledge and information [294]. Therefore, the collaborative relationship between the industry and academic forms an important element in exploring the potential of energy saving with Big Data analysis. However, the concern of data-sharing in every organization has become a barrier to establish academic collaboration and implementation of new technology [295]. To form a healthy collaboration, both parties have to establish a common understanding of possible challenges resulting from operation structure, culture and constraint [291]. The challenges and conflicts are identified to maximize collaboration output in Table 12.

The collaborations between academics and industry are very important to create new innovative solutions and data exchange. In the data-driven era, the barrier and gap between the industry and academics are mainly challenged by the lack of talent, suitable collaboration partner and the infrastructure of data processing. In order to address the challenges in energy sectors using data-driven approaches, the contextual understanding should be established. The proper policy and agreement shall be in place to avoid unnecessary misunderstanding where data-driven policy is concerned.

6. The way forward

The future for data-driven energy savings for Industry 4.0 is bright and promising. However, certain efforts from researchers, industrialist and policymakers will certainty accelerate field developments. From the perspective of researchers, more research effort is required in addressing the full data pipeline which includes data acquisition, data cleaning, modelling and industrial implementation. The responsibility of researchers in this field includes:

(i) Provide more low-level research and halt discrimination on "data janitor"-type research.

Table 11
Advantages of academics and industry from collaboration.

Benefiting Party	Advantages	Source
Academics	Access to industry funding	OECD [282]
	Access industry equipment and patent	Barnes et al. [283]
	Commercialization of research idea	Perkmann et al. [284]
	Leverage on industry requirement to train future talent	Deloitte Global and the Global Business Coalition [285]
	Access to industry insights and operation data	Sannö et al. [286]
	Enhance R&D facility and capability	Grimpe and Hussinger [287]
	Improves the university's reputation	Van Rijnsoever et al. [288]
	Academic aims to publish finding at reputable journals to be the outstand their competitor.	Newberg and Dunn [289]
Industry	Leverage on expensive research infrastructure	Ankrah and Al-Tabbaa [277]
	Access to high-quality talents	Myoken [290]
	Access to high-technology and knowledge	Barnes et al. [283]
	Low-risk exploration study	Wallin et al. [291]
	Commercialization of patent and IP	Han [292]

Table 12
Academic and industry collaboration: challenges.

Barrier and challenges	Academic	Industry
Data access and handling	Energy consumption behaviour varies with industry sectors, the researchers need access to reliable real-time industry data to produce impactful outcome [296].	Kaisler et al. [297] highlight the concerns over ownership of data where the data privacy is concerned. Industries are not technological and physically ready for Big Data such as upgrading IT infrastructure, developing new cultures and new employee skillset [298]. Lack of expert in data-driven technology in the organization [299]. Many energy-related organizations are not aware of their capability and competency in handling Big Data especially in electricity, oil and gas and transportation sectors [300].
Project schedule	Academic are exploring for long term collaboration to develop, explore and validate the energy-saving model. The inflow volume of data is too huge where the researcher needs to invest in proper data storage management especially in the non-IT sector such as energy [301].	Industries are looking for short term outcomes to maintain their position in the market [302]. The industry expects positive research outcomes to be produced in order to be ahead of their competitors.
Relationship	Long term collaboration [303] especially on the researching funding aspect [282].	Howells et al. [304] highlighted that some industries have problems accessing the university's knowledge and information as they do not have any contact with the university. Establishment of collaboration is highly depending on the university's expertise, capability and infrastructure of laboratories that align with the industry's direction [305].
Resource	Support from Academic is restricted by the university's schedule. For example, the usage of expensive lab infrastructure is highly depending on the availability of the equipment [277].	Industries are looking for high availability of support from the academic [306] such as human resource [290] and laboratory [307]. The bargaining power, financial power and setback handling from research outcome differ with the scale of the company [303].
Expectation	Funding from the industry is an important, industry data and data validation	Develop talent, technology and commercial able solutions. Data security is lagging falling from the current research ecosystem [301].

(ii) Focus on realistic industrial implementations instead of pseudo-theoretical problems.
(iii) Accelerate development in enabling technologies.
(iv) Carry out more interdisciplinary collaborations and communications.

As the implementation of data-driven energy-saving systems will be physically within the industrial area, industrialists also play an important role in the future development of this field. The responsibility of industrialist includes:

(i) Respect research advances from the academic world and participates in collaborations.
(ii) Provide honest feedback and problems to researchers.
(iii) Allocate funds for R&D projects and technological transitions.
(iv) Enhance information infrastructure and data collection methods within the facility.

Project economics is one of the bigger constraints for both academics and industrialists. Contrarily, the task for policymakers to encourage industrialists and researchers to further develop novel industrial systems that can contribute to global energy savings and energy efficiency elevation. The responsibility of policymakers is less in quantity, but significant in quality, which includes:

(i) Provide effective funding schemes for academic-industrial energy-saving projects.
(ii) Encourage energy audits and regulate policies to favour advanced energy-saving systems.

With concise cost and energy consideration, the development of digital twin-based infrastructure will pose to be a beneficial step in the fields of energy development for mankind. It will be thrilling to see what future technological development will be unveiled to us soon.

7. Conclusion

This paper discusses that the future of digital twin-based infrastructures for data-driven energy savings remains optimistic. As SCADA system remains the *de facto* standards in typical industrial facilities, there are many industries that have incomplete data acquisition systems due to the costs of implementation. A potential solution for low-cost data acquisition with high coverage is by using IIoT sensors. However, the connection reliability of such devices needs to be improved by using 5G connections as redundancy. For this matter, more technological development is required to lower the costs of devices and shorten the roll-out timing for industrial implementations. This paper also points out the importance of modularizing and standardizing data infrastructure during implementation. Moreover, there are many limitations in these directions, such as ensuring the reliability of sensor devices, balancing the accuracy in simulation and optimization of digital twins, bounding the complexity of the computation, and putting all the data infrastructure together within feasible investment costs. Hence, the timeliness of research in this field is critical towards its significance and relevance. In terms of digital twin modelling, data sensor integration, data security, computational and data storage services, there are already many commercial services that can support the implementation. Nevertheless, this paper recommends that further developments in the fields of AI, Blockchain 3.0, 5G-enabled IIoT, Digital Twins are essential to accelerate research advances in the practical implementation of this field. In utilizing such technologies for energy saving, there is international interest in the forms of government initiative and policies (in regions such as Europe, United States, China, India, Malaysia, etc.) that can support smart energy-saving projects. Future developments in the field require close communication and collaboration between academic researchers, industrialists and policymakers. To secure an energy-sustainable future, each party should provide responsible collaboration and contribute to their speciality. A strong symbiosis between multiple parties in a multi-disciplinary setting will contribute greatly to the success of digital twin-based infrastructures for data-driven energy savings. To conclude, the novelty of this paper is that the current context of industrial energy-savings was extended towards a more digitalized paradigm for smart industrial energy-saving in Industry 4.0.

Credit author statement

Sin Yong Teng: Conceptualization, Investigation, Writing-Original Draft, Writing- Review & Editing, Visualization. **Michal Touš:** Conceptualization, Investigation, Writing – Original Draft, Project administration. **Wei Dong Leong:** Conceptualization, Writing – Original Draft, Writing - Review & Editing. **Bing Shen How:** Writing – Original Draft, Writing - Review & Editing, Visualization. **Hon Loong Lam:** Supervision. **Vítězslav Máša:** Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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