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The Impact of Intelligent Cyber-Physical Systems on the Decarbonization of Energy

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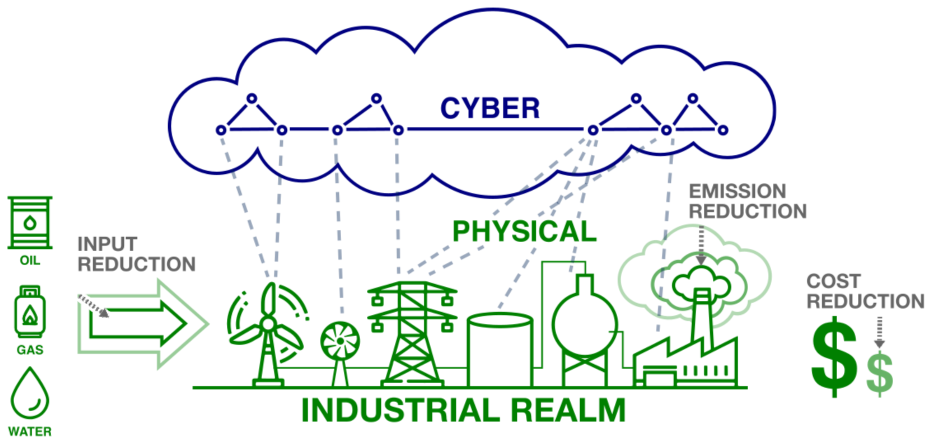
Abstract

The decarbonisation of energy provision is key to managing global greenhouse gas emissions and hence mitigating climate change. Digital technologies such as big data, machine learning, and the Internet of Things are receiving more and more attention as they can aid the decarbonisation process while requiring limited investments. The orchestration of these novel technologies, so-called cyber-physical systems (CPS), provides further, synergetic effects that increase efficiency of energy provision and industrial production, thereby optimising economic feasibility and environmental impact. This comprehensive review article assesses the current as well as the potential impact of digital technologies within CPS on the decarbonisation of energy systems. *Ad-hoc* calculation for selected applications of CPS and its subsystems estimates not only the economic impact but also the emission reduction potential. This assessment clearly shows that digitalisation of energy systems using CPS completely alters the marginal abatement cost curve (MACC) and creates novel pathways for the transition to a low-carbon energy system. Moreover, the assessment concludes that when CPS are combined with artificial intelligence (AI), decarbonisation could potentially progress at an unforeseeable pace while introducing unpredictable and potentially existential risks. Therefore, the impact of intelligent CPS on systemic resilience and energy security is discussed and policy recommendations are deducted. The assessment shows that the potential benefits clearly outweigh the latent risks as long as these are managed by policy makers.



Highlights

- Review of cyber-physical systems and their role in decarbonisation of energy systems.
- Utilising the marginal abatement cost curve (MACC) for the quantification of the impact of cyber-physical systems and artifical intelligence.

Contents

1 Introduction

1.1 Energy system transition

Transforming the global energy system is a challenging trade-off between advancing economic competitiveness and safeguarding the environment. Ensuring worldwide access to affordable, reliable and sustainable energy is a specific requirement of the United Nations Sustainable Development Goals (SDG) [176]. Against this backdrop, reducing CO_2 emissions from energy systems is of vital importance in order to adopt a sustainable development pathway. The Paris Agreement suggests that limiting the global temperature increase to 2°C requires over 300Gt cumulative CO_2 reductions from the energy sector by 2050 [82]; whereas the recent IPCC special report on the 1.5°C pathway demands an even more radical reduction of fossil fuel generation from the current level of 65% to 8% in 2050 [52, 87]. Achieving such a rapid decarbonisation of energy systems requires not only disruptive energy-technology innovations but also a fundamental revision of how our energy system should be designed, operated and optimised to maximise the emission reduction potential without affecting security and resilience of supply [3, 186]. It has been widely acknowledged that a successful energy system transition requires combined efforts of technological progress, economic innovation, policy intervention and behavioural change throughout the energy landscape [166]. Among such transition processes, several perspectives are particularly promising and therefore have attracted significant research interest, for instance low-carbon power provision and energy efficiency enhancement. Furthermore, the adoption of decentralised generation and storage in energy systems has blurred the distinction between traditional producers and consumers, resulting in so-called "prosumers" - entities that both produce and consume energy. Such a decentralisation also increases the complexity of the energy system, for instance because the traditional linear supply chain for energy (generation-transmission-distribution-consumption) will continue to evolve into a complex, intertwined and interdependent network [34]. In summary, we are at a critical point in the transformation of our energy system from traditionally separated energy silos and linear supply chains into interconnected complex systems with interacting components and stakeholders. Therefore, the identification of open questions and potential solutions for this critically important transition presents energy researchers with unique opportunities. This comprehensive review and impact assessment will explore the role of digital technologies in the transition process - *vide infra*.

1.2 Cyber-physical systems

The main objective of this paper is conceptualising the different developments of digital technologies and their impact on energy systems with specific focus on environmental sustainability and economic feasibility [83]. A list of critical digital technologies and related application examples is shown in Table 1. Although digital technologies have been classified into various categories in Table 1, in practice these different technologies are typically intertwined with each other in specific applications. For example, advanced metering infrastructure (AMI) is an important source of big data in energy systems, whereas analysis of big data could be conducted through machine learning (ML). Similarly, the Internet of

Table 1: *Selected cyber-physical technologies and their applications in energy system.*

CPS technology	Definition	Applications in the energy transition
Big Data	Data set with high volume, high velocity and high variety [37]	Big data driven energy management system [201] (see Section 3.2)
Machine Learning	Computer programs that can access data and use data to perform tasks without being explicitly programmed [65]	Intermittent renewable and demand forecast [5] (see Section 3.1)
Internet of Things	Network of connected devices that could collect information about the real world remotely and share it with other systems and devices through Machine-to-Machine communication [70, 175]	IoT enabled appliances control in smart home [147] (see Section 3.2)
Advanced Metering Infrastructure	An integrated system of smart meters, communications networks and data management systems that enables two-way communication between utilities and customers [41]	Advanced metering infrastructure based demand side management [167] (see Section 3.2)
Edge Computing	Edge computing, often occurring on distributed CPUs embedded in executing devices such as robotics (*i.e.* at the extremes of the network) [152]	Hierarchical distributed edge computing framework architecture for smart cities [169] (see Section 3.4)
Blockchain	A non-centralised digital transaction ledger that is public [123]	Encrypted ledger for peer-to-peer energy trading [154] (see Section 3.3)
Smart Contracts	A smart contract is a computer protocol intended to digitally facilitate, verify, or enforce the negotiation or performance of a contract [71]	Smart contract based decentralised transactive energy auctions [71] (see Section 3.3)
Semantic Web	Semantic description, understanding and integration of data on the World Wide Web [17]	Ontological knowledge management of district energy system [195] (see Section 3.4)
Digital Twin	Virtual representation of physical entities in cyberspace [153]	Predictive maintainance of offshore wind farm in cloud-based platform [64] (see Section 3.4)

Things (IoT) can create a scenario where data sharing through the semantic web is crucial to create virtual representation of physical entities in a digital twin. In order to bridge this conceptual gap in digital technologies applications, the concept of cyber-physical systems (CPS) has been adopted as a high-level combination of the aforementioned digital technologies [192]. CPS are therefore the orchestration of linked computers and physical systems both horizontally (within a physical system and computer respectively) and vertically (integration between a physical system and computer). In this paper, CPS are defined as co-engineered interacting networks of physical and computational components [124], while the actual methodologies are referred to as subsystems. CPS aim to create a virtual representation (cyber-space) of real entities (physical space) to seek optimal solutions to real-world problems by exploring solutions in the cyber-space. In addition, artificial intelligence (AI) can be combined with CPS to add intelligent decision-making capability, evolving CPS into so-called intelligent CPS; herein shown in Figure 1. This integration of intelligent CPS in energy systems could not only change their design principle and operation regime, but also contribute to their transition in many ways; examples of such intelligent CPS benefits include energy efficiency enhancement [196], operational flexibility in a dynamic environment [131], resilience of critical infrastructure [192] and more. A recent IEA report points out that "digitally interconnected systems could fundamentally transform the current energy industry"[83]; the newly launched US Department of Energy's Clean Energy Smart Manufacturing Innovation Institute (CESMII) also supports the future integration of smart manufacturing and the energy industry, of which one important aspect is exploring the possibility of using smart manufacturing conceptions to improve the efficiency and sustainability of the energy industry [47]; in the European Strategic Energy Technology Plan (SET Plan), digitalisation is also considered a revolutionary and unavoidable enabler of the transition of the energy sector [164]. As a result, it is urgent to initiate a thorough discussion of how intelligent CPS technologies (*e.g.* IoT, AMI, ML combined with AI) can be applied in the energy system transition to improve its economics, sustainability, resilience and safety, while catalysing decarbonisation endeavours (Figure 1).

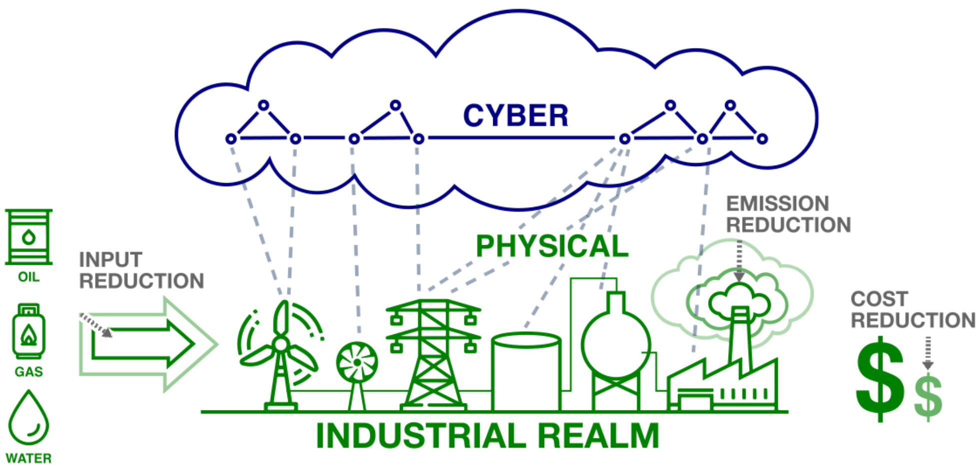


Figure 1: *Architecture of intelligent cyber-physical system.*

1.3 Scope of the paper

In light of the two aforementioned contexts, this paper strives to present an impact assessment of CPS technologies on the transformation of energy systems, while focusing on enabling technologies, potential applications, influence on energy system economics and environmental sustainability as well as energy security. Section 2 provides a review of the state-of-the-art of the predominant transition processes for energy systems. Section 3 lays out how CPS are affecting these trends using several representative examples of CPS applications, such as intermittent renewable integration, demand side management and efficiency enhancement. Section 4 reviews the impact of intelligent CPS on the economic viability and resilience of energy systems and deducts policy implications from this socio-economic analysis. Finally, Section 5 assesses the potential of intelligent CPS for emission reduction, economic optimisation as well as the security and resilience of the future energy system.

2 Energy system transition: State-of-play

Although the predominant opinion sees CPS technologies as important catalysts for the evolution of energy provision, such changes can only happen with a rigorous understanding of the state-of-play of the transition process and a purpose-oriented design of CPS that does not jeopardise systemic resilience [158]. Therefore, a systematic review of the transition process is presented in this section: major energy transition trends (*e.g.*low-carbon power provision, energy efficiency improvement, energy storage adoption) are summarised, while the main barriers for these technology applications and their cost-effectiveness are pointed out hereafter.

2.1 Low-carbon energy provision

A breakdown of the global power generation mix in 2017 is shown in Figure 2. It is evident that fossil fuel still dominates the power sector at present; although the EIA reference-scenario projects a two-fold increase of renewable generation by 2050, it is still far from the requirement under the IPCC 1.5°C pathway [52, 87]. Moreover, in the IPCC scenario, a rapid switch from fossil fuel is specified with annual generation from coal, gas and oil dropping from 9669 TWh, 5360 TWh, 813 TWh in 2017 to 223 TWh, 2061 TWh, 15 TWh in 2050 respectively (Figure 2). In order to achieve such a goal, fossil fuel power plants need either early retirement or integration with means to sequester produced greenhouse gases underground [26].

Carbon Capture and Storage It has been pointed out that early retirement of fossil fuel power plants is difficult to achieve due to significant institutional inertia in the regulatory bodies and long infrastructure lifetimes [35, 55]. As a result, major hopes have been placed on carbon capture and storage (CCS) as an enabler for continuous utilisation of fossil fuel in future low-carbon scenarios. *Energy & Environmental Science* has published a series of papers on CCS regarding its technical, economic and commercial challenges to which the interested reader is referred to for more in-depth views. [23, 74, 163]. Although

CCS could have a unique role in reducing the carbon intensity of power systems, especially in scenarios with a long time horizons, it has to be noted that the rhetoric on CCS has not been turned into reality so far (at the time of writing, there are only two operating CCS projects in the power sector worldwide with total capture capacity of 2.4 million tons per year [9]). Even though the technology readiness level of power plant post-combustion CCS has already reached the commercial level (TRL9) [26], CCS integration into a typical coal power plant would result in a two-fold increase of generation costs, resulting in a CO_2 abatement cost of around 40US$/ton [1], thus undermining the economics of fossil fuel power plants in competitive electricity markets. Enhanced oil recovery – the draining of oil wells through sequestration of carbon dioxide – could provide additional incentives for CCS deployment, yet upscaling of CCS from megatonnes to gigatonnes to produce material climate change mitigation effects still faces high uncertainty from carbon pricing, technology learning and fuel prices [101].

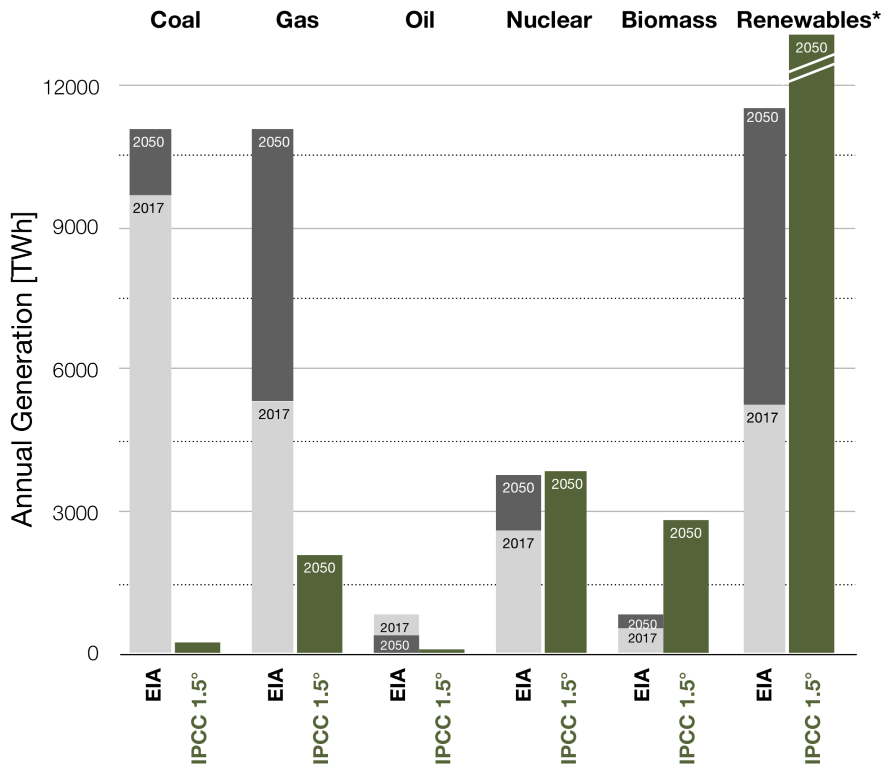


Figure 2: *Global power generation mix in different scenarios. EIA reference scenario (left column) with world economic growth at 2.8 percent per year from 2015 to 2050 and crude oil price at $119 per barrel in 2050 [52]; IPCC scenario (right column) corresponds to the 1.5°C pathway of global warming. IPCC scenario provides a range with uncertainty [87]; only the case with total generation equal to 2050 EIA scenario is shown.*

Renewable Energy - Biomass: Compared to CCS adoption, the provision of renewables

[1]Coal power plant average generation cost are 82US$/MWh and 48US$/MWh with and without CCS, respectively [117].

is a more sustainable, long-term solution for the energy system transition. Renewables are divided into biomass and non-biomass (*e.g.* solar, wind, hydro power, geothermal and tidal power). Combustion of biomass is considered as carbon-neutral due to the atmospheric CO_2 sequestration capability of biomass. Potential assessment of biomass-enabled decarbonisation in energy systems is challenging for two main reasons. Firstly, the availability of the primary energy supply of biomass is a complex function of land use, water use, food supply, agricultural efficiency and biodiversity [44, 156]. Secondly, optimal allocation of biomass between different end users (*e.g.* electricity, heat, transportation fuel and most importantly food and feed) is a non-trivial problem that needs global optimisation with many case-dependent parameters [79], for example geographical distribution of biomass supply [58]. A recent analysis shows that biomass could provide 20EJ (*e.g.* 5500 TWh) 2050 power supply in the 2°C Scenario [2] (2DS) with total biomass availability of 112EJ [160]. Such a projection would be more than enough to cover the biomass supply requirement of the IPCC scenario in Figure 2; however, cost-effectiveness evaluation of such biomass deployment has not yet been conducted [185].

Combined Biomass and CCS: Integrated biomass and CCS, known as BECCS, is a negative emission technology that is included in many mitigation pathways. Opinions around BECCS are controversial: although many treat BECCS as effective technology to offset carbon emission overshoot [19, 148], others argue that incorporation of BECCS and other negative emission technologies into the emission pathway could postpone the deployment of non-biomass renewables [179] and result in risky carbon lock-ins due to issues with the BECCS scale up (around 16000 BECCS power plants are needed in 2050 under the 2DS pathways whereas there are only three industrial demonstrations at the time of writing [108]).

Renewable Energy – Wind and Solar: In order to compensate for these biomass-related limitations, non-biomass renewables, mainly solar and wind, are needed [73]. Solar power capacity has witnessed a substantial leap during the past decades: solar PV capacity has increased from 1234 MW in 2010 to 384621 MW in 2017, whereas concentrated solar power (CSP) has increased from 419 MW to 4952 MW during the same period [85]. As a consequence, the average generation cost of PV was reduced by 73%, from 360USD/MWh to 100USD/MWh [85] and in case of CSP the generation cost was reduced by 33%, from 330USD/MWh to 220USD/MWh between 2010 and 2017. Although the low end of utility-scale solar PV cost has been reported at 36USD/MWh [105], the general competitiveness of solar PV in the generation market still heavily relies on policy incentives, such as feed-in tariffs (FIT) and investment tax credit (ITC) [104]. Similar trends can be found for wind energy – the global capacities for both onshore and offshore wind generation have multiplied between 2010 and 2017, with a 30-fold increase from 16863MW to 494821MW for onshore wind, and a 280-fold increase from 67MW to 29726MW for offshore wind. Simultaneously, the average generation cost decreased from 80USD/MWh and 170USD/MWh in 2010 to 60USD/MWh and 140USD/MWh in 2017 for onshore and offshore wind respectively. Wind generation costs have been reduced to 29USD/MWh for specific cases [105], yet these low-end costs can only be achieved when the weighted average cost of capital (WACC) is low and operating conditions such

[2] The 2DS lays out an energy system pathway and a CO_2 emissions trajectory consistent with at least a 50% chance of limiting the average global temperature increase to 2°C by 2100 [84].

Table 2: *Cost and emission performance of selected power supply technologies.*

	Levelized cost of electricity (2016USD/MWh) Min/Median/Max			Life cycle emission (gCO_2 eq/kWh) Min/Median/Max
	IPCC estimations[a]	IRENA estimations[b]	LAZARD estimations [c]	IPCC estimations[a]
Coal-PC	30/67/104	-	60/-/143	740/820/910
Coal-PC-CCS	62/120/164	-	-	190/220/250
Gas-CCGT	34/78/153	-	41/-/74	410/490/650
Gas-CCGT-CCS	49/94/208	-	-	94/170/340
Nuclear	35/71/103	-	112/-/189	3.7/12/110
Biomass	69/142/295	50/70/140	-	130/230/420
Hydropower	7/24/104	20/50/220	-	1/24/2200
Geothermal	13/66/142	30/70/140	71/-/111	6/38/79
Solar PV	61/120/142	50/100/350	36/-/46	18/48/180
CSP	120/164/241	160/220/260	-	9/27/63
Wind onshore	38/65/131	40/60/280	29/-/56	7/11/56
Wind offshore	87/131/197	110/140/240	29/-/56	8/12/35

[a] IPCC estimations assume 5% WACC and high full-load hours (*i.e.* capacity factors), 2010 USD is converted to 2016 USD using an inflation calculator from [88, 177]; [b] International Renewable Energy Agency (IRENA) estimations present results based on global weighted average plant data [85];[c] LAZARD estimations mainly focus on optimistic market in U.S., therefore its estimations on renewable cost is relatively lower [105].

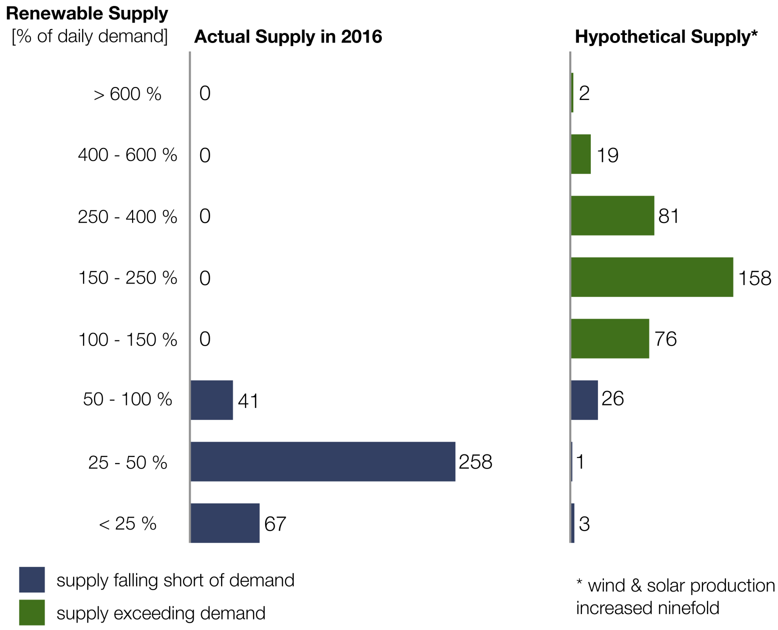


Figure 3: *Daily power demand versus renewable supply balance for Germany. Shown here is the percentage of renewable energy supply in daily demand during different days in 2016 (left); on the right is a hypothetical scenario where renewable capacity increased by nine times such that renewable energy supply is only insufficient for 30 days through the year.*

as capacity factors are favourable [42]. All estimations referred to above by IRENA and LAZARD are summarised in Table 2. Another challenge for solar and wind is their inherent intermittency: both sunlight and wind exhibit natural temporal fluctuations and ancillary generation and storage capacity are needed to handle the imbalance between supply and demand [111]. As a result, in absence of sufficient storage capacity, solar and wind energy can only provide 25%-50% annual energy demand, even in countries with high installation capacity [69]. A recent analysis for Germany shows that renewable energy capacity needs to be increased by nine times to make renewable supply sufficient over most of the year [90, 149] (Figure 3). It has been pointed out that CPS, in particular ML applications, can facilitate such alignment between supply and demand from various aspects, such as solar and wind variability prediction or coordinated model predictive control [83]. A detailed discussion on these perspectives will be provided in Section 3.1.

2.2 Energy efficiency

Increasing Energy Efficiency: In addition to adopting low-carbon technologies in generation portfolios, increasing energy efficiency is key for moving towards cost-effective, low-carbon energy provision: the latest IEA study estimates that 40% of global CO_2 emissions could be reduced through energy efficiency improvement [84]. Industry, transportation and the building sector have been identified as key areas to further enhance energy efficiency and representative examples are provided in Section 3.2. For energy-intensive industries, such as steel and iron, pulp and paper and petrochemicals, increasing energy efficiency could be achieved through various technologies. One of the most promising is introduced hereafter [189].

Supervisory control and data acquisition (SCADA), manufacturing execution system (MES) and enterprise resource planning (ERP) are widely used in industry to monitor the production process, facilitate the operation and maintenance of industrial processes, and thus reduce energy consumption [114]. Similarly to industry, the building sector harbours great potential for improving energy efficiency using a home energy management system (HEMS) [199]: HEMS can monitor and schedule home appliances based on user patterns and real-time electricity prices, improve renewable penetration by coordinating supply and demand forecast, and support diagnosis of building energy systems, particularly HVAC system operation [109]. Considered more broadly, connected HEMS can aggregate to become a so-called System-of-System (SoS) to reduce the peak energy demand of buildings in communities and cities; such demand side management capabilities of HEMS will be detailed in the next section as well. For the transportation sector, strategies for improving the energy efficiency of traditional fuel vehicles include fuel economy regulation and tailpipe emission control [193]; yet in the long run, the shift from internal combustion engines to electric drivetrains (EV) for cars and light-duty vehicles is a more sustainable path for low-carbon mobility [89]. Previous studies have shown that the well-to-wheel CO_2 emission of electric vehicles largely depends on the generation portfolio of electricity grids [77], so increasing low-carbon generation in the electricity mix is critical and therefore discussed in Section 2.1. Furthermore, the interaction between electric vehicles and the grid has great impact on the design and operation of power grids. On one hand, EV battery charging could change the load curve of a power system thus requiring electricity capacity expansion [191]; on the other hand, the plug-and-play operation model of vehicle-to-grid (V2G) could make it a potential spinning reserve for the frequency control of distribution grid [129]. In this case, EV fleet management systems have to have access to system-wide information sharing and distributed control to provide charging strategy optimisation, individual mobility modelling and V2G scheduling among others. CPS would clearly be a highly valuable asset for such an optimisation.

Alternative Approaches: Circular economy (CE) provides another important perspective to further improve energy efficiency. As an alternative to the traditional linear make-use-dispose economy, this approach utilises material recycling, re-manufacturing and energy reuse to effectively avoid resource waste, thereby improving energy efficiency and industrial sustainability [110]. Based on the principles of CE, industrial symbiosis (IS) and eco-industrial parks (EIP) have become popular industry cluster initiatives in many countries: in Kawasaki Japan, reusing industrial wastes in cement manufacturing has reduced 15% of greenhouse gas emissions since 2009; in Karlsruhe Germany, energy exchange between neighboring companies results in 21% carbon emission reduction [68]. The current EIP optimisation approaches for optimal design of water, energy and material network integration only focus on single-styled resource networks; in order to reach an optimum symbiotic relationship among industries, all resources need to be taken into consideration simultaneously. Moreover, variability of resource supplies should be addressed in more realistic models because of the inherent uncertainties of related processes. As a result, integrative decision support tools are needed to facilitate data sharing between different end users [67]. Similarly, CPS provides significant opportunities for energy efficiency

Table 3: *Technical, economic and energetic performance of selected bulk energy storage technologies.*

	Round-trip efficiency (%)	Power specific capital cost (\$ per kW)[a]	Energy specific capital cost (\$ per kWh)[a]	Energy return on investment (kWh per kWh)[b]
Pumped hydroelectric	75-80	1500-2000	10-100	704
Compressed air	55-70	850-1200	200-250	797
Pb-A battery	75-90	450-650	300-450	5
NaS battery	75-85	350-800	250-400	20
ZnBr battery	60-75	500-1500	200-400	9
VRB battery	65-80	1000-1500	200-600	10

[a] Power and energy specific capital cost data are taken from the estimations by [146]; [b] Energy return on investment (EROI), more precisely as energy stored on investment (ESOI), is taken from analysis by [14].

improvement through enhanced energy management frameworks, which will be shown in Section 3.2.

2.3 Energy storage

Storage Technologies: Storage is another important dimension of the energy transition. The necessity for energy storage is tightly related to the temporal and spatial imbalances between supply and demand in energy systems, particularly in the case of intermittent renewables (current power grid stability without storage would be jeopardised with more than 20% intermittent renewable [69]). Different storage technologies could add value to multiple points in the electric grid; examples of such benefits include capacity adequacy and energy arbitrage through bulk energy storage, load following, spin/non-spin reserve and frequency response [12]. A range of energy storage technologies (chemical, mechanical, thermal and electro-chemical) have been proposed and assessed in the literature [32, 162]. However, similarly to CCS, the theoretical potential of various energy storage options has not yet been fully realised: according to the global energy storage database in 2016, the vast majority of global energy storage capacity (*e.g.* 162.2GW out of 168.6GW) is fulfilled by pumped-hydroelectric storage, which is a fully developed technology with significant geographic constraints [127]. Although pumped-hydroelectric storage has a relatively high power rating and discharge time, it only has an energy density of around 1Wh/kg; comparatively, a state-of-the-art lithium-ion battery could achieve energy density of 200Wh/kg and minute-level discharge capability [32], which can play the role of spinning reserve in modern electric grids [12]. A comprehensive comparison of various energy storage technologies with regard to their power rating, discharge time, lifetime, self-discharge rate, energy and power density, efficiency and response time is conducted in reference [69]. The scientific consensus is that there is currently no silver bullet in energy storage technologies: to meet the different needs of grid electricity storage, portfolios of energy storage technologies have to be developed and tailored to the specific needs of the respective electricity grid.

Grid Balancing: In the first instance, energy storage technology could be used as bulk energy storage in power grids. Bulk energy storage typically refers to large-scale energy storage on the scale of hundreds of megawatts capable of continuous power provision for multiple hours [146]. Important benchmark metrics for bulk energy storage technologies are investigated in literature based on economic and energetic analysis (Table 3). It can be seen from this table that compared to batteries, mechanical energy storage technologies (*e.g.* pumped hydroelectric and compressed air) have a significantly lower energy specific capital cost ($ per kWh) and higher energy return on investment (*i.e.* the ratio of power stored over the lifetime of the storage device to the embodied energy required to build the device). It can therefore be concluded that battery storage still has a huge economic and energetic gap compared to pumped hydroelectric and compressed air for bulk energy storage. A recent study points out that substantial bulk energy storage is only necessary when a near-zero emission energy system is pursued and a high carbon price is imposed, otherwise dispatchable gas turbines could provide enough flexibility in a power system [146]. Based on such investigations, there are still open questions around whether bulk energy storage is an economically and energetically competitive way to decarbonise the energy system, how much bulk energy storage is needed for different decarbonisation targets of the energy system and how it should be properly valued and paid off.

Electricity Arbitrage: The utilisation of temporal price discrepancies in the electricity market using storage capacity, so-called electricity arbitrage, is a common value-added service related to bulk energy storage. The benefits of energy arbitrage vary by region and market (from $1 per kW-year to $163 per kW-year) [12] and it is known that the foreknowledge of real-time energy prices has a huge impact on the benefits of energy arbitrage, CPS enabled electricity market design could therefore play a vital role in energy arbitrage through Machine-to-Machine (M2M) communication and automated trading. More perspectives on this aspect will be put forth in Section 3.

Ancillary Services: With the exception of bulk energy storage, energy storage technologies could also provide ancillary services in power grids such as voltage support, spinning/non-spinning reserve, black start and frequency response. Different performance requirements in terms of discharge and response times are required for different services [69]. Furthermore, electrical energy storage technologies could be used in power transmission and distribution systems to facilitate congestion relief and upgrade deferral, and on the customer side to improve power reliability, reduce power demand and eliminate power outages [12]. Detailed discussions on how energy storage should be designed, operated and valued in these applications are beyond the scope of this work [97]; instead, the focus of this study centres on how CPS innovations could facilitate energy storage integration into an energy system during the energy transition stage. Details will be discussed in Section 3.3.

Power-to-X: The integration between electricity and other energy carriers (*e.g.* heat or fossil fuel) also provides significant opportunities for energy storage. Instead of power-to-power conversion in power grids, power-to-X (P2X) enables the storage of electricity in other energy carriers. Some pilot examples include power-to-heat (converting power to heat through heat pumps), power-to-gas (converting power to hydrogen through electrolysis), power-to-fuel (manufacturing methane/methanol/syngas and other chemicals based on hydrogen and CO_2), and power-to-mobility (EV) [10, 162]. There are several benefits of P2X: firstly, electrification has become a major trend in primary energy utilisation, yet

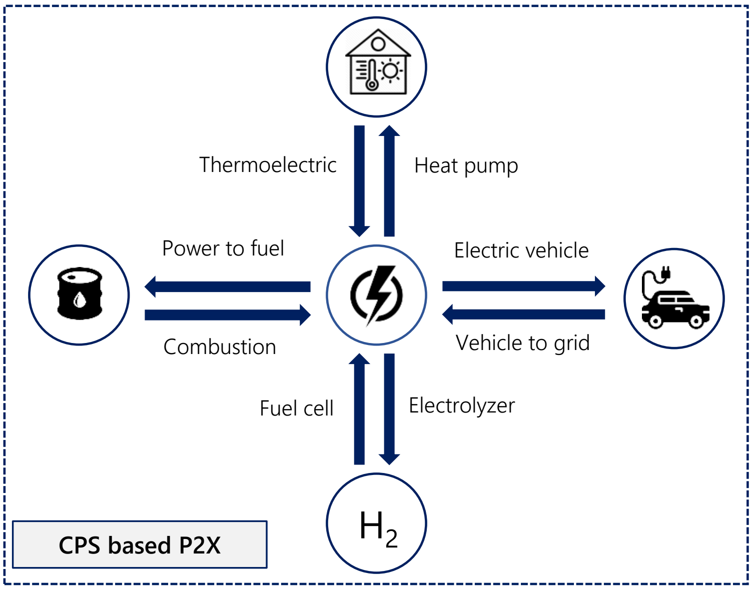


Figure 4: *Schematic of various Power-to-X (P2X) technologies applied in an energy system. Shown in the figure are different technologies that could convert electricity into other energy end users (e.g. heat, gas, fuel and mobility) and vice versa.*

there are certain difficult-to-electrify sectors including the aforementioned heating, transportation and chemical industries [36] of which P2X assists with decarbonisation through sector coupling. Secondly, integrated electricity, gas and heat networks could provide additional flexibility for power utilisation [98] – energy could be stored with a longer time scale (*e.g.* seasonal or annual) via thermal, gas, or chemical pathways [190] and transportation of gas and chemicals through existing infrastructure provides another way to balance the spatial and temporal mismatch between supply and demand in energy systems [159]. Comparisons of different P2X pathways in terms of energetic, economic and environmental impact have been conducted in different studies: a comparative assessment shows that power-to-heat and power-to-mobility through electric vehicles have relatively higher environmental benefits compared to power-to-gas and power-to-fuel in terms of global warming impact and fossil depletion impact [162]. Meanwhile, net energy analysis in another study suggests that power-to-gas through regenerative hydrogen fuel cells has a higher energy return on investment (EROI) compared to battery because of the low energy cost of hydrogen storage material [135]. In the case of the power-to-fuel pathway, it is also pointed out that combining low-carbon electricity from renewable and CCS for methanol production is an inferior mitigation option compared to independent CCS and renewable power utilisation in terms of CO_2 mitigation potential and cost [1]. A similar argument is supported by the analysis of different pathways for electrochemical synthesis of liquid chemical from CO_2; the results show that none of these processes could compete with the present fuel prices based on traditional manufacturing processes [157]. Based on such studies, it can be seen that the environmental benefits and economic costs of P2X projects should be carefully evaluated based on the specific application context. Intelligent CPS-enabled energy system design and optimisation could contribute to the solution of such problems; its potential is detailed in Section 3.3.

2.4 Energy management

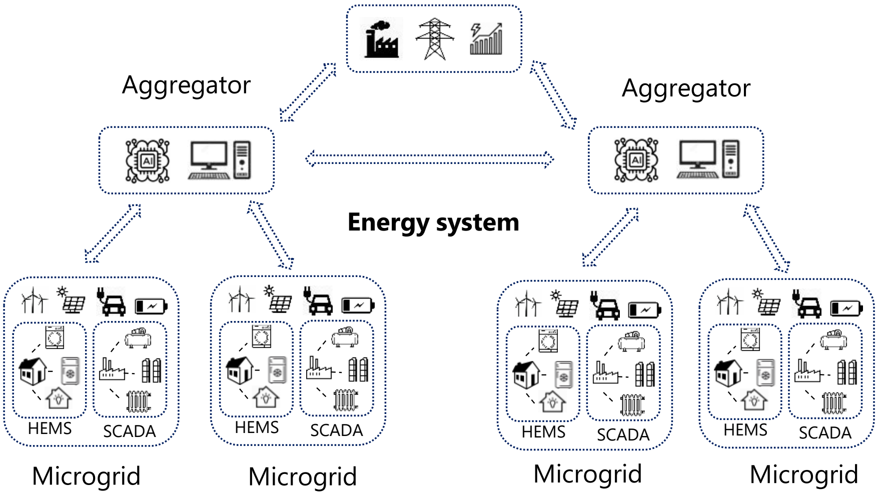


Figure 5: *Schematic of a CPS-enabled hierarchical energy management system. Shown in the figure is a hierarchical structure of an energy management system enabled by the two-way communication between HEMS, SCADA, microgrid and aggregator.*

Energy Management Systems: Systematic activities, procedures and routines including the elements of strategy planning, implementation operation, control, organisation and culture involving both production and support processes, which aim to continuously reduce energy consumption and its related energy costs, are defined as energy management systems (EMS) [151]. These systems pose another great challenge in the transition to sustainable energy provision. As the definition implies, EMS need a hierarchical framework to facilitate the communication between interacting elements in the system. A schematic of such a hierarchical EMS is shown in Figure 5. From this figure it can be seen that the increasing adoption of advanced metering infrastructure (AMI) in home energy management systems (HEMS), together with data-driven decision support, could allow billions of collected appliances to be involved in demand response [83]. Specifically, in the context of HEMS, the energy management system could receive price signals from system operators or aggregators, which could be treated as moderators between the grid operator and end users. According to the embedded computational algorithms, the energy management system would make decisions on how different appliances should be scheduled in order to get maximal incentive without undermining normal function. Sequentially, the control orders could be sent to different appliances from the energy management system through AMI so that the orders are implemented in different appliances. Aggregators play a key role in such CPS-enabled demand response. Like the virtual power plant, aggregators could bundle groups of customers, possibly together with the related renewable and storage options under its management, and act as unified flexible sources in an energy system. Early demonstrations of such applications have been proposed; it is shown that for a population of 629 houses, 21% peak load could be shifted by combining dynamic pricing and HVAC system control [66]. Machine learning methods, especially reinforcement

Table 4: *Selected machine learning algorithms used in energy system literature.*

Algorithms	Definitions
Linear Regression	Discover linear relationship between output and one or more features [95, 182]
Curvilinear Regression	Find polynomial relationship between output and one or more features [95, 182]
Auto Regressive Integrated Moving Average	Coupled auto regression and moving average method in time series forecast [61, 139]
Decision Tree	Tree-like graph for classification [140]
Naive Bayes	Classification technique based on Bayes theorem [140]
Support Vector Machine	Use kernel method to transform the data then find the optimal boundary between outputs [5]
Random Forest	Get mean prediction through multitude of decision trees [5]
Artificial Neural Network	Regression or classification through interconnected nodes [141]
K-Nearest Neighbors	Learn feature probability distribution through distance function [141]
Principle Component Analysis	Reduce feature space dimension through orthogonal transformation [197]
Boosting	Ensemble meta-algorithm [143]
Markov Chain	Stochastic model describing a sequence of possible events [6]
Reinforcement Learning	Agent-based AI algorithm in which the agents learn the optimal set of actions through interaction with the environment [181]

learning methods, could make important contributions in the area [181]. A list of such algorithms is also shown in Table 4. It is expected that by using such ML algorithms in demand forecasting and dynamic pricing design, together with the proposed hierarchical CPS schematic, the potential of energy management systems could be fully unleashed in future energy systems, which will be discussed in Section 3.4.

Throughout Section 2, it was explained that the ongoing energy transition is a complex long-term challenge that needs collaborative contributions from low-carbon power provision, energy efficiency enhancement, storage adoption and other related areas. Despite the notable progress in these areas elaborated above, there is much work to be done to meet future energy targets. Intelligent CPS technologies, from a systematic perspective, could hypercharge such advancements therefore accelerating the energy transition. Hereafter, several "sweet spots" of intelligent CPS technology applications in energy systems will be analysed in the paper, including computer vision aided renewable resource identification, CPS-based building management system, CPS-enabled smart charging of electric vehicles, deep learning enabled data centre cooling control, agent-based modelling and integrated cross-domain platforms for energy management.

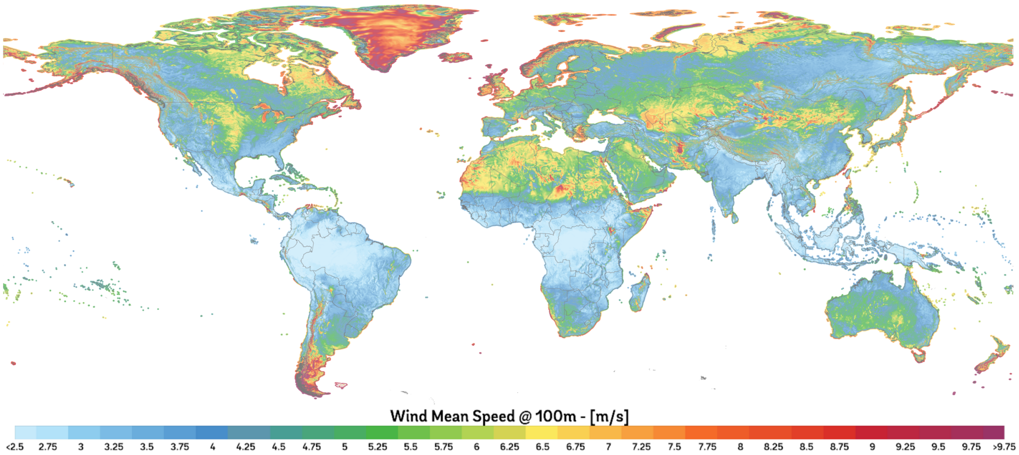
3 Intelligent CPS applications in energy transition

In Section 2, major trends in the transition of energy systems have been outlined on a conceptual level, while this section reviews in detail some applications of selected CPS technologies in this transition. Current applications of CPS technologies in energy systems cover various segments including generation, transmission, consumption and storage at various spatial levels (equipment, building, district, city [130]). Although the ultimate goal of CPS is to create a holistic platform that facilitates the design and operation of energy systems, this is not yet a reality and CPS applications are restricted to specific contexts, such as promoting low-carbon renewable integration (Section 3.1), increasing energy efficiency through demand side management (Section 3.2) and facilitating energy storage through electric vehicle charging (Section 3.3) [83]. In addition, opportunities and challenges for the future development of intelligent CPS technologies are discussed in this section as well (Section 3.4). Hereafter, prominent examples for the impact of CPS on energy systems are outlined.

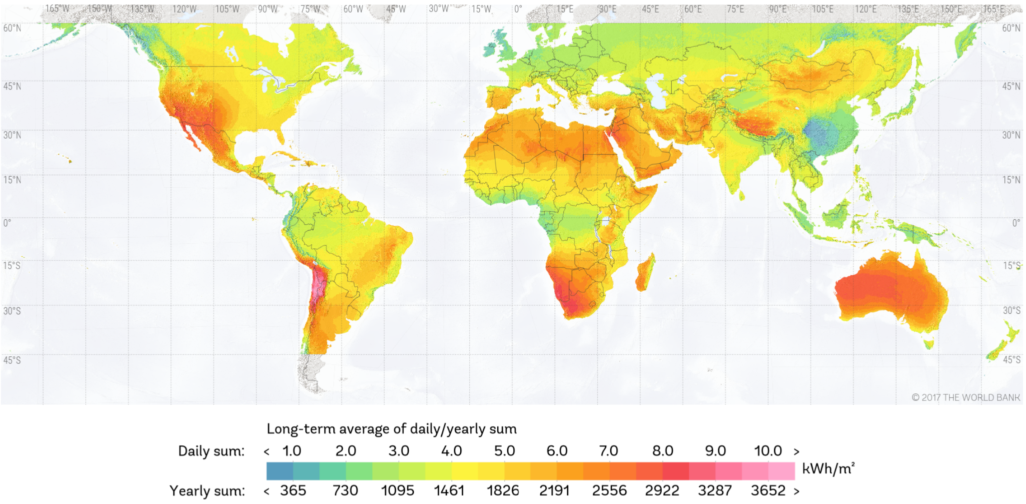
3.1 Promoting low-carbon energy provision

Improving CCS: The application of CPS technologies in CCS power plants can transform the vast amount of operational data into actionable intelligence in order to integrate and improve plant operations, thereby reducing costs and improving energy efficiency [142]. The I4GEN project, or Insight through Integration of Information for Intelligent Generation [49], defines three enabling technologies for such a transformation – real-time information, distributed and adaptive intelligence, action and response. It is also pointed out that six digital networks (sensors and actuation, data integration and information management, advanced process control, asset monitoring and diagnostics, advance O&M, optimisation) are important for such a digital transformation. In the first instance, the project demonstrates its capability in fault diagnosis through advanced pattern recognition algorithms, *e.g.* analysing turbine blades' vibration data to prevent turbine damage; analysing cooling tower motor temperature data to spot possible clogs. In the long run, it is anticipated that CPS technologies can be used for real-time monitoring of a CO_2 storage site as well as leakage detection through drones and computer vision [83]. Successful applications of machine learning-based computer vision in natural gas leakage detection have already been reported [184] and the possibility of using deep learning to classify methane leak sizes at oil and gas facilities has been proved as well [183]. The International Energy Agency estimates a 20% decrease in CCS plant operational costs based on observations at natural gas plants [83]. Based on these initial findings, it can be concluded that the application of CPS technologies in CCS storage and monitoring could enhance the economic feasibility of this approach to climate change mitigation and moreover, alleviate the energy drawbacks of the sequestration process.

Supporting Renewable Energy Provision: In order to bridge the gap between EIA projections and IPCC targets for renewable energy capacity (Figure 2 outlined in Section 2.1), the identification and projection of the global potential for renewable energy are of vital importance. Aerial photos and satellite maps provide useful information on this aspect and the combination of satellite data and numerical analysis methods for such an assessment



(a) *Global wind power resources in terms of mean wind speed at 100m height*



(b) *Global solar power resources in terms of direct normal irradiation*

Figure 6: *Global wind and solar power resources in terms of mean wind speed at 100m height and direct normal irradiation. Data obtained from the Global Wind/Solar Atlas, a free, web-based application developed, owned and operated by the Technical University of Denmark (DTU) in partnership with the World Bank Group, utilising data provided by Vortex, with funding provided by the Energy Sector Management Assistance Program (ESMAP) [53, 54].*

Figure 7: *Automated solar panel location and size estimation through deep learning techniques based on satellite imagery. On the left is the location and size of solar panels as detected by satellite imagery; on the right is the reconstructed image based on a deep learning method [194].*

has been proposed [170]. An example outcome of such an effort is shown in Figure 6. Here, the global potential for energy provision from wind and solar generation is shown; in the case of wind, its mean speed at 100m height is used as a proxy while direct normal irradiation is used to estimate the potential for solar power. These assessments are conducted based on high-resolution remote sensing and can provide important baselines for the planning of new solar and wind farm projects in terms of optimal location and potential capacity *et al.* [53, 54]. The Prediction of Worldwide Energy Resources (POWER) project by NASA is another effort in this area – by making use of NASA's satellite observations, the project can provide net solar radiation and meteorological data at high temporal and spatial resolutions (*e.g.* 0.5^o latitude/longitude and with hourly results [137]). With recent developments in machine learning, in particular deep learning, detailed useful knowledge extraction from such images becomes possible. For instance, it is reported that by exploring convolutional neural network (CNN) and concurrent local sky images, minute-level solar panel output predictions with around 30% relative-root-mean-square error values (rRMSE) could be achieved [168]. In another study, deep learning models are used for automatic detection of solar PV panel location and size based on satellite imagery; here, a nearly complete solar panel installation database for the contiguous US is established [194]. The input and output of such deep learning methods are shown in Figure 7. It can be seen here that the current deep learning techniques could accurately identify the solar PV panel location and size from complex satellite imagery in a fast and scalable way, thus providing updated information about rooftop solar PV installations. By further utilising socio-economic data, the model could correlate such factors with solar deployment to obtain useful insights and predictions on the current solar power capacity as well as key factors that could shape the future potential. Based on such insights, it is estimated that at least 8% more solar PV panels will be installed in the US [194].

In addition to the assessment of the potential for renewable capacity, intelligent CPS tech-

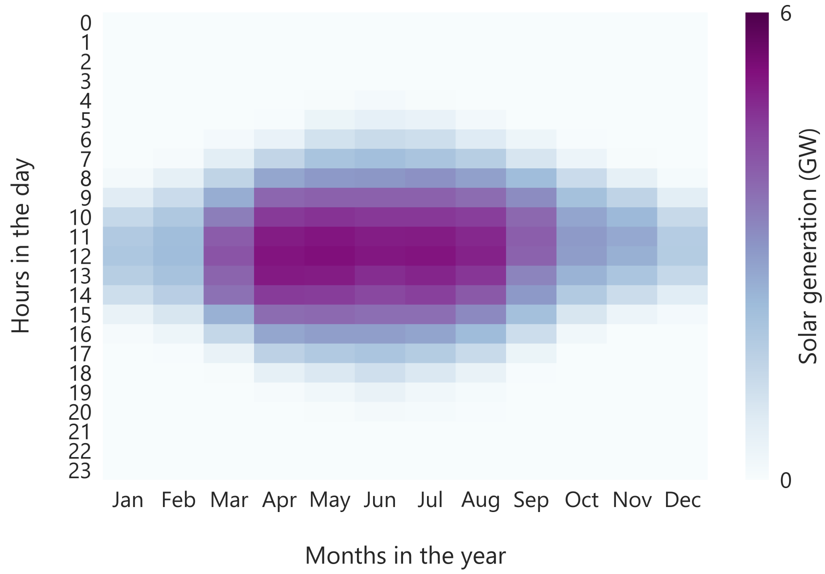
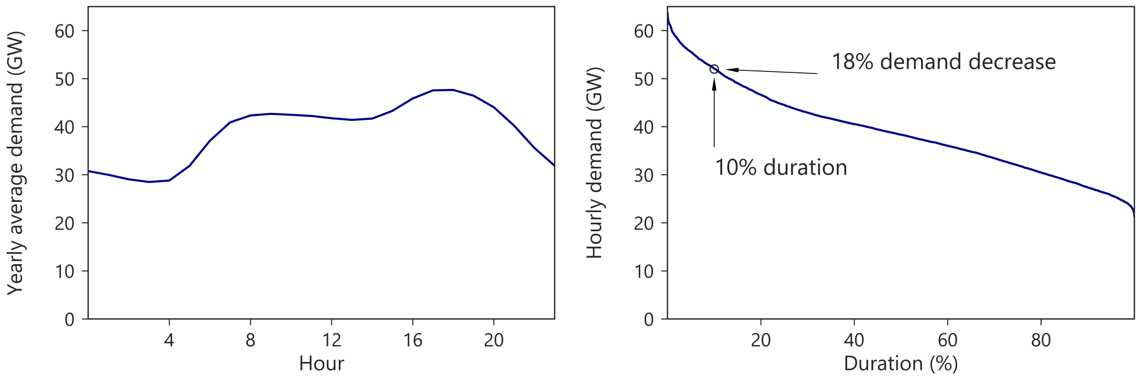


Figure 8: *Heat map of solar energy generation in the UK power system in 2017. Shown here is the UK power system average hourly solar power generation over 2017. Darker colors on the heat map represent higher values. Data shown in the figure is available from [63].*

nologies, in particular machine learning methods, can also facilitate the integration of intermittent renewables through improved forecasting of variability. As discussed in Section 2.1, the intermittent nature of renewable energy is a main barrier for its large-scale penetration of the energy system. For example, the hourly solar generation of the UK power system could reach 6GW during summer peak hours but remain at 2GW on most days in winter (Figure 8). As a result, a flexible natural gas plant is still needed in the generation mix as a supplement and backup for such renewables.

Augmenting Grid Balance: For the efficient operation of such mixed energy systems, accurate forecasts of renewable fluctuation at various time horizons (*e.g.* intra-hour, intra-day, day-ahead, week-ahead) are critical as they can contribute to efficient management by optimising unit commitment, economic dispatch and maintenance scheduling among other factors [182]. Recent advances in machine learning could play a major role in such areas. Compared to traditional physical methods like numerical weather prediction, ML methods could provide higher prediction accuracy at larger temporal and spatial scales (*e.g.* 1 second to 1 month, 1 m to 2 km [81]). Various ML methods have been applied in the area of renewable forecasting, among which the most commonly used include artificial neural network (ANN), k-nearest neighbor (KNN), support vector machine (SVM) and random forest [5, 61]. Selected examples of such algorithms and their definitions are provided in Table 4. Generally, the forecasting methods are divided into two categories: univariate methods that only use endogenous time-series data of previous power output, and multivariate methods that combine power output time series and exogenous data from numerical weather predictions and meteorological measurement [139]. While detailed descriptions of the models are beyond the scope of this paper, it is important to note that



(a) *Hours in a day versus yearly average demand* **(b)** *Duration percentage versus hourly demand*

Figure 9: *UK power system demand profile in 2017. Shown here is the yearly average power system demand for different hours in the day (left); on the right is the percentage that various hourly demand accounts for. As can be seen, the top 18% demand only lasts for 10% during the year [63].*

state-of-the-art forecasting methods can reduce the relative-root-mean-square error values (rRMSE) to 2% and 5% for day-ahead solar and wind forecasting respectively [143]. Such an increased prediction accuracy can economically optimise the operation of energy systems: it is estimated that by applying such forecast models, the Independent System Operator New England (ISO-NE), which operates a system with 13.5% solar power, could reduce its annual electricity generation cost by 13.2 million USD [113]. A similar conclusion is reached by the US National Renewable Energy Lab for California's Independent System Operator (CAISO), which operates with 25% wind. Here, it is found that a 10% forecast performance improvement could result in overall annual savings of 25 million USD due to reduced operation time of regulation reserve and renewable curtailment [76]. The potential benefits of renewable forecasting in other power systems depend on the specific generation portfolio structure as well as characteristics of the electricity market; moreover, it could be projected that as renewable share in energy systems increases, the benefits of ML-based renewable forecasting would be larger. In that way, ML-based renewable forecasting could become the next high value-adding point in future energy system operations.

3.2 Reinforcing energy efficiency

As laid out in Section 2.2, another area in which CPS technologies are highly likely to make a significant difference is increasing energy efficiency, for instance in real estate management or the efficient use of energy infrastructure.

Building Management Systems: In the building sector, CPS will transform operations when integrated into building management systems (BMS). The Brick schema is a representative CPS-based BMS application [11] in this area; its main purpose is to represent the contextual information of sensors, systems and building structures in existing building management systems (BMS) through class hierarchy (tag sets) and relationship sets.

The Brick schema is realised in a resource description framework data model that represents knowledge as triples: subject, predicate and object. The applications of such meta-data schema are shown through automatically converting raw BMS meter data into structured data complying to the Brick classes and integrating it with usable data analytical techniques for fault diagnosis in buildings. In particular, Brick schema applications allow us to conduct stuck damper detection by comparing supply air flow sensor values and system set points as well as to detect simultaneous heating and cooling by querying the reheat coil command and supply air flow temperature sensor of different variable air volume terminals feeding the same room. BOnSAI, a Smart Building Ontology for Ambient Intelligence, is another well-developed CPS application operating at the building level [161]. Similar to Brick schema, BOnSAI targets smart buildings, yet from the perspective of ambient intelligence (a ubiquitous, personalised, context-aware computing environment through embedded IoT infrastructure in buildings). The classes in BOnSAI are categorised into several main concepts: hardware, service and context. Hardware class describes the devices and appliances as part of the physical entities in buildings, such as air conditioner, lighting, sensor and actuator; service class describes the functionalities of devices as operations, with each operation having its own input, output, precondition and effect; context class describes the dynamics of different operations in different circumstances. Furthermore, BOnSAI was demonstrated to facilitate the coordinated control of SmartPlugs on a university campus by interpreting the sensor parameters at various locations.

Improved Utilisation of Energy Infrastructure: In addition to improved BMS, CPS can also contribute to the efficient use of expensive energy infrastructure through demand side management. The rationale behind demand side management is tightly related to the fact that the demand profile of most power systems is nonlinear; that is to say, high demand only happens during a short period of time all year round as shown in Figure 9. It can be seen that the top 18% demand only lasts for 10% of the year, resulting in a high peak-to-average ratio of the power system. Similar demand characteristics of other energy systems at different temporal and spatial scales have been reported [39]. In order to tackle such challenges, the conception of demand response has been proposed to reduce the peak-to-average ratio in power systems and has been implemented in various contexts: through demand response, the peak demand of CAISO, ISO and New England have been reduced by 1500 MW, 530 MW and 1100 MW respectively [96]. The latest IEA report estimates a 185 GW flexibility benefit by implementing demand response worldwide, which could result in around 270 billion USD savings by avoiding investment in new electricity infrastructure [83]. The potential for demand response could be realised through two approaches: price-based schemes and incentive-based schemes [165]. In the price-based approach, a dynamic pricing mechanism is designed so that end users could adjust their load schedule accordingly. Examples of such dynamic pricing schemes include time of use rates (TOU), critical peak pricing (CPP), real-time pricing (RTP) *etc.* In contrast, in an incentive-based approach, participating customers are obligated to change their consumption pattern as required and receive an incentive/punishment for their response/inaction [200]. In both cases, a major challenge is that two-way communication between consumer and utility is needed in order to both pass the price signal to consumers and collect power consumption data from different end users [40]. As a result, most existing price-based demand side management projects are designed for energy-intensive industry and commercial end users because of the relatively high energy intensity and existing communication infrastructure (*e.g.* the supervisory control and data acquisition system mentioned in Section 2.2). CPS provides a new paradigm for such EMS including big data driven analytical frameworks (BDDAF) and AI-based solutions for energy-intensive industries. BDDAF has been proposed as architecture for future industry EMS, which strives to connect high-resolution process simulations with real-time data by taking advantage of IoT and distributed artificial intelligence [198]. Successful examples of such CPS based EMS in improving the energy efficiency of industrial processes have been reported in literature [47]. In Germany, it is estimated that demand side management potential from energy-intensive industries, such as wood pulp production, aluminum electrolysis and cement mills, could reach 1230MW in 2020 [132].

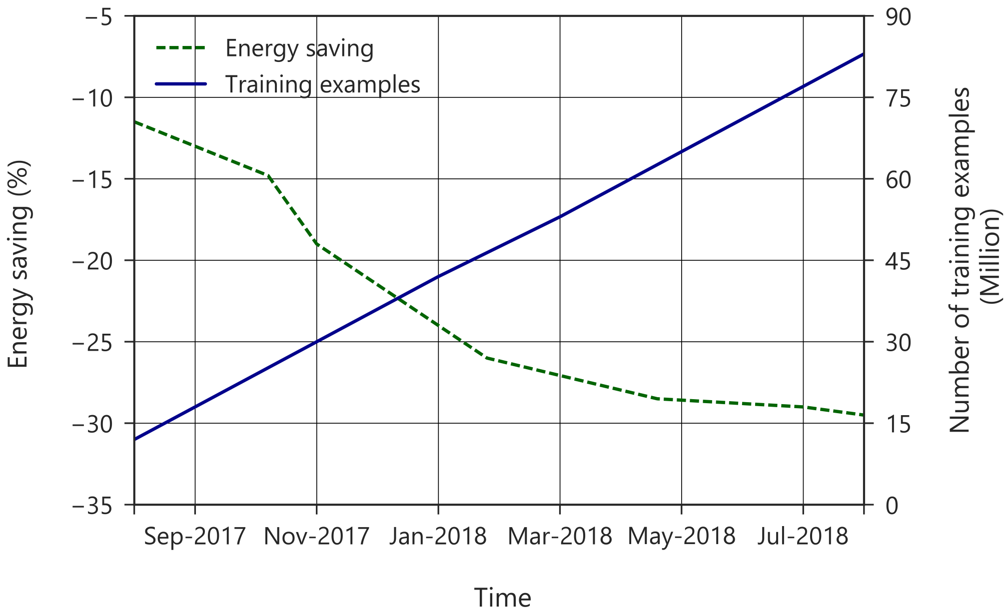


Figure 10: *Performance of Deepmind AI system in cooling control of data centre. Shown in the figure is the change of energy saving (green) and number of training examples (blue) of a data centre cooling control AI system enabled by deep neural network [57].*

The recent development of *deep learning* has been successfully implemented in energy efficiency improvements [106]. DeepMind, the company behind AlphaGo, has developed an AI system which was used for data centre cooling control [57]. Control of data centre cooling is difficult due to the complex interaction between equipment and environment as well as the unique architecture and environment of each data centre. As a result, traditional rule-based engineering and heuristics do not work optimally in these cases [16]. To address such a complex problem, DeepMind has developed a deep neural network-based algorithm for efficient and adaptive optimisation of the energy efficiency of Google's data centres. Trained with historical data that has been collected by various sensors, the AI system can reduce energy demand from data centre cooling by 30% (green line in Figure 10). Moreover, an internal list of safety constraints has been proposed to guarantee that the optimal actions computed by AI are vetted; operators of the data centre could also exit the AI mode at any time if safety concerns are raised. The self-learning nature of the deep neural network also enables performance improvements by AI over time with increasing data availability (blue line in Figure 10), and therefore further efficiency gains are highly likely. The efficiency gains outlined above have economic and environmental ramifications which will be addressed in Section 4.1.

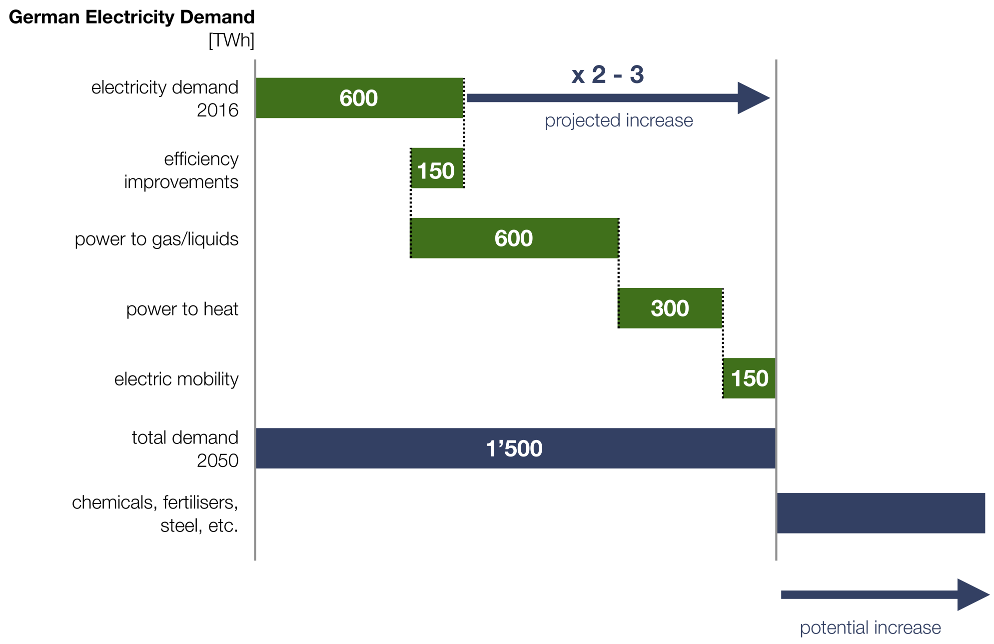


Figure 11: *Predicted electricity demand increase in Germany from 2016 to 2050 due to sector coupling between electricity sector and other end users [].*

3.3 Facilitating energy storage

As mentioned in Section 2.3, P2X enables coupling between the electricity and other sectors, such as transportation, heating and cooling, and fuels as well as chemicals. Although "electrification of everything" combined with low-carbon power generation provides a theoretical pathway to a net-zero-emission energy system [36], it would simultaneously induce a significant increase in electricity demand. For instance, it is estimated that by introducing power-to-gas, power-to-heat and power-to-mobility applications in Germany, the total electricity demand would increase by two to three times from 2016 to 2050 (Figure 11). In such a context, it is important to design novel strategies that utilise synergetic effects throughout the integrated energy supply chain as shown in Figure 4. Intelligent CPS technologies can therefore play a vital role in the holistic design and control of such integrated energy systems.

Coordinated Charging: CPS-based smart charging of electric vehicles is a good example of such synergetic applications. The expansion of the EV market in the coming years will result in a significant increase in EV charging-related power demands, but such an increase can be flattened out by implementing advanced charging control [38]. Achiev-

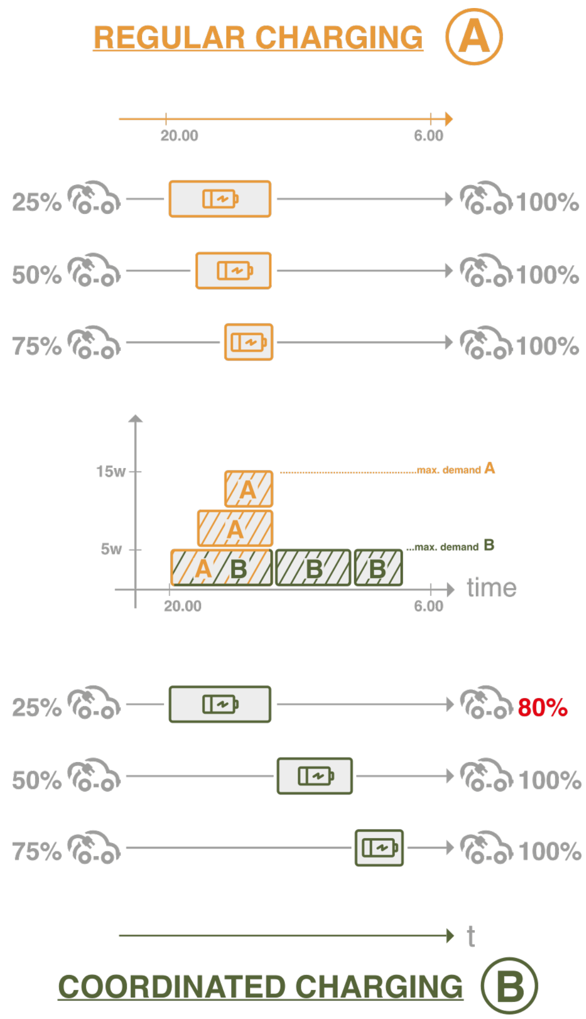


Figure 12: *Impact of regular and smart charging strategies on the peak power demand. Shown in the figure is the comparison between regular and smart charging and the resulting EV charging demand; peak power demand can be reduced significantly by combining mobility data and the distributed control method.*

ing such a goal requires a coordinated smart charging strategy; the schematic of a CPS-enabled smart charging scheme is shown in Figure 12. It can be seen from this figure that by combining mobility data, EV battery characteristics and distributed intelligence, the peak power demand resulting from EV charging could be significantly reduced. In the illustrated scenario, it is assumed that three different charging stations are responsible for three different EVs which come to the charging stations at different times with different loads. In the conventional "park and charge" scenario, the EVs would be fully charged once they reach the charging station; in such a scenario, the aggregated power demand from EV charging is 15kW at maximum (Figure 12, orange line). In the "smart charging" scenario, the vehicle would provide the charging station with its energy needs for the coming day [191], and the intelligent CPS would use the data from all vehicles to design a charging schedule that smooths demand and utilises the lowest possible electricity prices; peak demand would be reduced to 5 kW (Figure 12, green line). The possibility of such a smart charging strategy has been proven in the Pecan Street Project, a US Department of Energy's Office of Electricity Delivery and Energy Reliability funded Energy Internet demonstration project in Austin, Texas [134]. The project physically connects over 1000 residences with smart energy, gas and water meter data. The smart meter data holistically covers the home's electricity use data at the individual circuit level as well as solar PV generation and EV charging. The temporal resolution of the data collection process could be as high as one second. The Pecan Street Project demonstrates that wireless IoT data acquisition and storage techniques combined with robust data backhaul and server-side data storage and manipulation can lead to improved solutions. By analysing the Pecan Street data, researchers have gained new insights about the optimisation of EV charging [121] and storage integration solution, increasing the feasibility of EV applications while minimising grid impacts [13]. Moreover, its technical solution of data collection, cleaning, sharing and analysis, although mostly commercially confidential at present, sets up a proper prototype of how a smart charging strategy can be implemented in reality. Recent studies have shown that in more complex scenarios, the benefits of such coordinated EV charging become larger: in the case of the UK power system with a hypothetical 10% market penetration of EVs, uncontrolled EV charging could result in an 18% daily peak demand increase whereas coordinated smart charging would only result in a 10% peak demand increase [138]. Similar patterns have been found for other P2X applications, for example, for power-to-heat applications in the German energy system, coordinated optimisation based on distributed information could reduce peak power demand by approximately 20% compared to uncoordinated operation [22]. In the same way, the increase in peak power demand caused by electrolysers in power-to-hydrogen applications can be mitigated by generating accurate hydrogen demand forecasts which allow for optimised incorporation [38].

Peer-to-Peer (P2P) Energy Trading: This is another area where CPS technologies can aid the integration of energy storage. One key dimension of the current energy transition is the creation of prosumers that directly participate in distributed production, consumption and storage. However, the distributed energy resources are mostly intermittent, and thus a transaction-based energy market is needed to enable trading between prosumers – so-called P2P energy trading [120]. The establishment of such a P2P energy trading platform provides an additional lever utilised towards the implementation of effective energy storage. Blockchain technology, especially when combined with smart contracts, is a promising technology to address the challenges of P2P energy trading through transparent, tamper-proof and secure systems [4]. Although the development of blockchain-enabled P2P energy trading and storage has not yet been widely applied, there are already multiple explorations in the literature: blockchain-enabled P2P electricity trading in the chemical industry has been successfully demonstrated where two electricity producers and one electricity consumer can trade with each other [154]. The possibility of combining such blockchain-enabled energy trading with an automatic price predictor for energy arbitrage is also reported [155]. A further study has proven that smart contracts can manage the auction throughout the bidding and energy exchange with multiple consumers bidding for PV power [71]. The benefits of such blockchain-based platforms have also been reported: in Romania, a blockchain platform that enables bilateral transactions between consumers and renewable energy producers could achieve up to 30% reduction in energy costs, whereas 40% savings is reported for another decentralised platform for energy trading between generating units and consumers in Slovenia [51]. Again, the full potential of such CPS-based P2X and P2P can only be unleashed if privacy and security issues can be overcome, a topic that will be discussed in Section 4.

3.4 Integrated energy management

Apart from the various CPS applications that have been proposed in the previous section, a promising direction for future CPS application in the energy transition is integrated energy management. Compared to CPS applications in the single domain, integrated energy management usually requires cross-domain interaction with other sectors of the economy, which would bring additional barriers stemming from the following aspects – data collection, communication, information exchange and data analysis.

Data Collection: The 3V (high volume, high velocity and high variety) characteristics of big data (Table 1) present practical problems in terms of data storage, processing and manipulation in CPS applications. Firstly, in modern smart meters, the temporal resolution of data collection could be as high as one second; such data sets could easily reach terabyte scale in the short term [201]. As a result, it is important to find an optimal way to store the data either locally or in the cloud [91, 112]. Moreover, CPS data are characterised not only by their large volume but also by their high heterogeneity [195]. CPS data are highly heterogeneous in both format and semantics. Data from different sources (sensors, texts, web, *etc.*) could be presented in completely different formats (tables, figures, natural languages, math equations, *etc.*). Moreover, such data could also be semantically not interoperable [11], as domain knowledge is only known implicitly to domain experts and different domains might refer to the same conception as different silos and *vice versa*. To some degree, overcoming this data heterogeneity is more challenging than handling the 3V data challenge in energy system CPS [118].

Communication and Information Exchange: As per the communication layer, data heterogeneity is also a significant issue that can affect communication performance and the design of communication protocols. Yet another challenge is balancing these privacy concerns and personal data control during communication with the possibility of accessing data to provide better services. Because CPS manages large amounts of data, including sensitive information like health, gender and religion, significant issues about data privacy are raised [75]. CPS requires privacy policies in order to address privacy issues, thus a data anonymisation management tool is required to produce anonymised information before the system processes it [40].

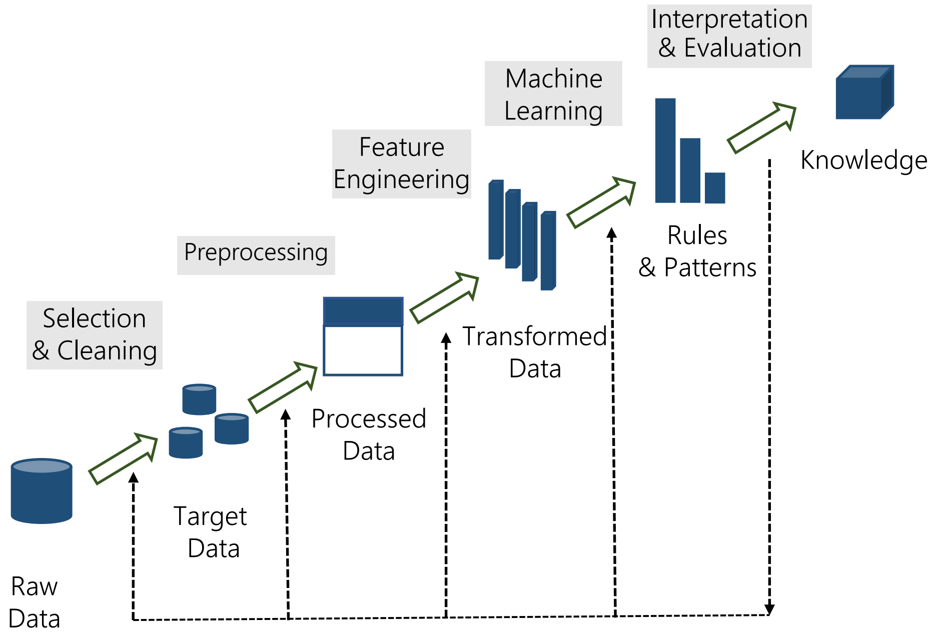


Figure 13: *A typical procedure of knowledge extraction from data through machine learning.*

Data Analysis: Gathering insights from big data through machine learning is a core competency in many CPS applications and computational intelligence plays a key role during such a process (Figure 13). Recent advances in machine learning techniques, especially deep learning, open new possibilities for such data-driven approaches in many energy system contexts [107, 196]. However, most ML models are black box and have low interpretability [29], whereas most existing energy management systems are rule-/logic-based [126]. As a result, a combination of such machine intelligence and prior expert knowledge in energy CPS projects poses another great challenge. Another concern in the computation aspect comes from the computational cost. Many ML models are quite computationally expensive and relatively slow, which could impose barriers for real-time applications such as parameter updating and model predictive control [150]. From such a perspective, it is expected that the future computational engine in CPS energy systems could balance domain knowledge and machine intelligence in a delicate manner such that best performance could be achieved with a modest computational cost.

Integration: Cooperation and coordination between different components in the energy system as well as between the energy system and other sectors (*e.g.* transportation, water, food) is a key feature of future energy systems[7]. To achieve maximal synergy of such an integrated system, a holistic optimisation framework is needed. Such integration needs much more than data assimilation; in most cases, interoperability between tools and models is essential [65]. However, most models currently available only contain a description of mathematics without methodologies, making it difficult to understand how the model should be reused and under what conditions the models are valid [102]. Only by changing such model representation standards, together with the incompatibilities between platforms and communication technology, problem-solving strategy in a distributed and coordinated manner could be formulated so that integration within the energy system could be realised [93].

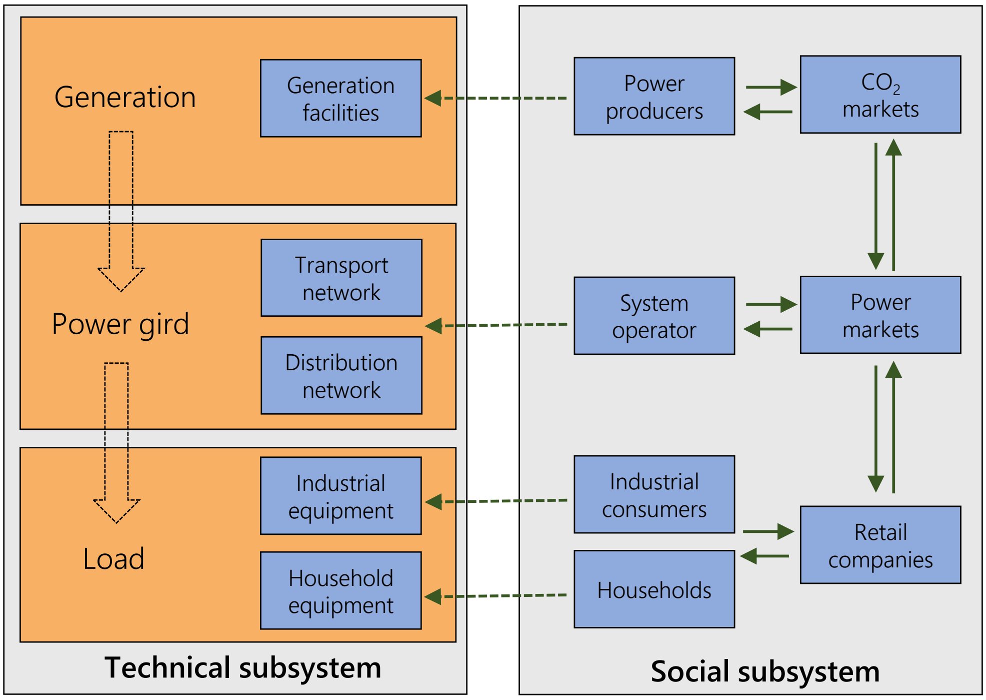


Figure 14: *Various interacting players in the social-technical subsystems of a power system as a typical complex adaptive system [178].*

Upgraded Urban Management: Agent-based modelling (ABM) is another commonly used method for such integrated energy management problems [178]. The interaction between different socio-technical players in a power system makes it a typical complex adaptive system, which features heterogeneous, interacting and adaptive units as well as emergent properties [145]. In Figure 14, different players in a power system (*i.e.* power producer, system operator, consumer in the social subsystem) are modelled as different agents that have their corresponding physical assets in the physical subsystem. By simulating the separate and interacting decision-making of different agents, system-level dynamics could be evaluated using an "assemblage" approach [31]. By combining GIS-based temporal and spatial information representations, ABM can link high-level master planning and low-level project planning for resource and infrastructure planning. Furthermore, by combining ABM and mathematical programming (*e.g.* linear programming, nonlinear programming), resilient and sustainable urban energy system planning can be achieved [20]. Digital city exchange is a pilot project in this area [78] (Figure 15) that aims to revolutionise the urban infrastructure by integrating energy, transport, waste and utility resources. The project takes advantage of recent progress in pervasive sensing, large-scale modelling, new optimisation techniques, web services technologies, the Internet of Things and cloud computing to find innovative solutions to optimise the use and planning of cities. Specifically, the projects look into the following aspects: sensor and data, cross-sector integration, real-time data incorporation and digital services implementation. Key findings of the project include urban sensor data integration techniques [25], design of reliable communication networks for sensors [125] and the interaction between behavioural economics and transportation energy consumption [2]. For such a project, it is estimated that peak power demand can be reduced by 20% by deploying the dynamic pricing based on such a demand response [131].

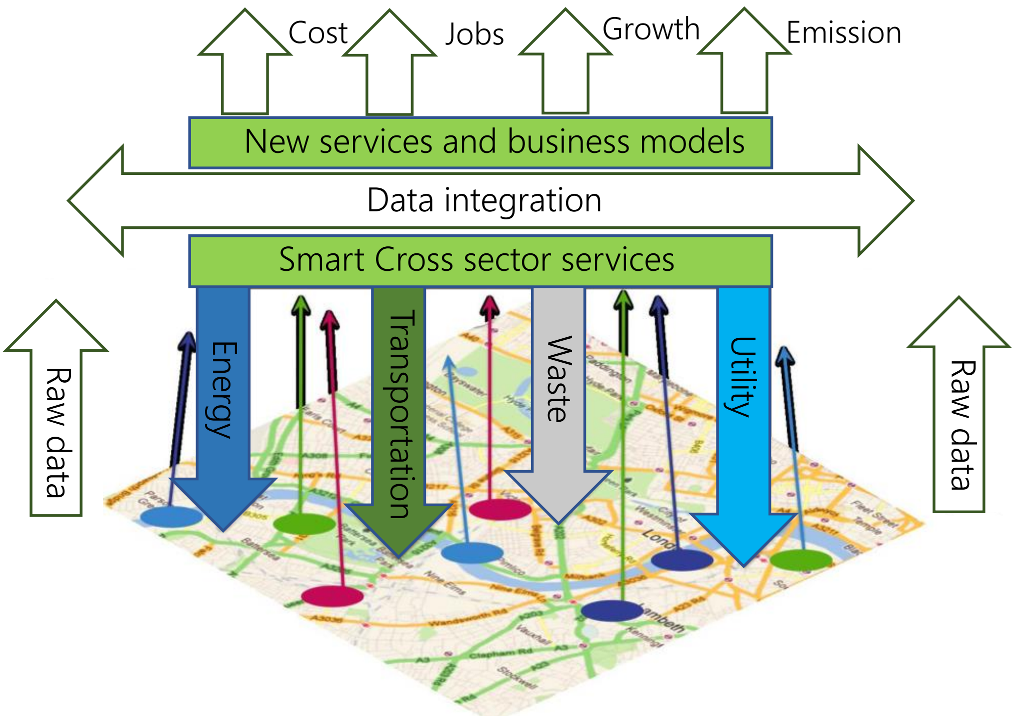


Figure 15: *Schematic of digital city exchange: An integrated platform for energy, transportation, waste and utility planning through pervasive sensing, large-scale modeling, new optimization techniques and web services technologies [78].*

Enhanced Management of Industrial Complexes: Increasing the reusability and interoperability of CPS subsystems is another challenge for CPS-enabled large scale energy system applications. J-Park Simulator, a general cross-domain platform used for energy management of large-scale energy systems based on distributed knowledge graphs and interoperable agents, provides some useful insights [195, 202, 203]. The Knowledge Graph represents a collection of interlinked descriptions of entities and aids the CPS with regard to data management, while agents are the executive subroutines of the CPS algorithm. The architecture of the J-Park Simulator is shown in Figure 16. In order to achieve high interoperability between different models and sub-systems, modular ontologies of various domains have been used. Some of the domain ontologies have been adopted, some have been obtained from the Linked Open Data Cloud and others have been developed as part of the JPS project. Such ontologies contain explicit descriptions of notions (concepts) for different domains so that heterogeneous data from different sources can be integrated into an interconnected knowledge graph. For example, in Figure 16, OntoKin contains ontological descriptions of chemical reaction mechanisms (which could be used for calculating emissions from combustion in engines or chemical processes in the atmosphere) [59]; OntoCAPE has detailed information about the energy conversion unit, equipment and process [119]; the weather ontology, DBpedia and OntoCityGML provide information about weather, common sense and urban infrastructure respectively [8, 99]. A key difference between a knowledge graph and classic relational database is that both data (instances) and concepts are represented by unique IRI which can be easily extended, both in terms of instances and concepts. The semantic representation allows logical operations on the elements of the knowledge graph. The operations on the knowledge graph are carried out by agents that are also described in form of concepts and instances. This facilitates interoperability between different domains, for example electricity and steam networks [195]. Based on such a knowledge graph, agents – namely "a physical or virtual entity that can act, perceive its environment (in a partial way) and communicate with others, is autonomous and has skills to achieve its goals and tendencies" – [60], can retrieve information from knowledge graph, perform specific tasks, interact with each other in a distributed manner and find an optimal solution to energy system design and operation problems. Several agent types have been proposed in order to tackle the inherent complexity of the energy systems.

Through the combination of the aforementioned types of agents, J-Park Simulator can automatically formulate solutions for different energy system related problems, such as optimal economic dispatch of power flow [144], industrial symbiosis network optimisation [203] and waste energy utilisation [195]. It is shown that by optimising the power and heat cogeneration system on Jurong Island Singapore, the annual power generation can be reduced from 19 TWh to 12 TWh, a reduction of 63% [144].

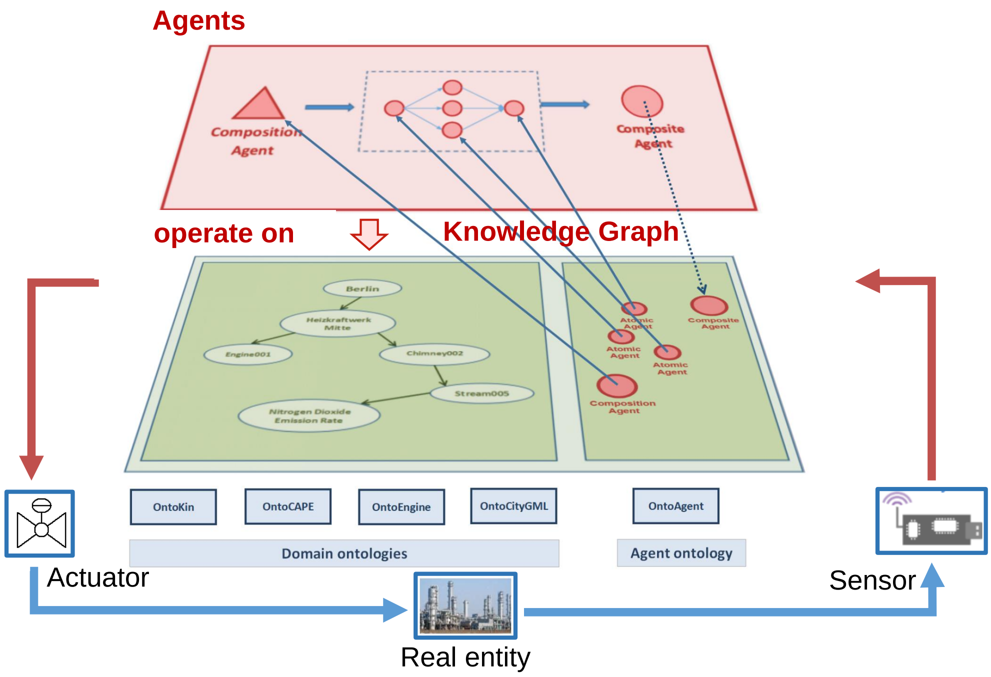


Figure 16: *Architecture of a cross-domain platform for energy management of a large-scale energy system based on distributed knowledge graph and interoperable agents.*

Through discussion of the above projects, it can clearly be seen that the applications of CPS technologies in energy systems have grown significantly over recent years while the complexity of the associated problems has grown simultaneously. The integration of CPS technologies into energy systems has changed from inarticulate to ubiquitous, adding a new dimension to the ongoing energy transition. As a result, contemporary energy systems are evolving from a purely physical to a cyber-physical system. This evolution generates a fully digital representation of the physical world in cyberspace. Studying the interaction and mutual impact of cyber and physical elements in energy systems has a significant impact on the economic, security and resilience of future cyber-physical energy systems, which will be detailed in the next section.

4 Impact of cyber-physical systems on the energy transition

The previous sections have illustrated that CPS are critical for the transformation of centralised, high-carbon energy systems to decentralised, low-carbon energy provision. Associated with this transition are costs as well as benefits, because significant investments in sensing and computational models precede the benefits arising from more efficient resource use and lean operations. In the subsequent section, the implications of three distinct, critical areas are addressed-economics, security concerns and policy. While there are obviously no holistic studies on the economic and policy implications of CPS, many clear conclusions can be drawn.

4.1 Economic and environmental impact assessment

The electricity sector is going through a significant digital transformation as traditional boundaries between the various branches of energy supply sectors like heating, cooling and transport begin to blur. Moreover, established conceptions of energy markets, business models and consumption patterns are being turned upside down and new providers, such as platform technology from other sectors, are already entering the market [115]. In addition to the current transformation challenges, new technologies are impacting internal business culture, strategies and the general management of the energy companies in an ever faster cycle. For instance, global investments in digital electricity infrastructure and software increased by 20% per annum in 2017 [83]. The economic rationale behind these investments is clear: the cost savings potential of CPS and its subsystems is estimated to be in the area of 80 billion USD between 2016 and 2040. Most of the reduction potential is due to reduced operations and maintenance costs, efficiency improvements, and reduced downtimes and prolonged lifespans [83]. According to the IEA, the following four areas are the main contributors [83]:

1. Smart demand response by preserving energy consumption and massive investment in new installed electricity supply capacity;

2. Integration of intermittent renewables;

3. Advanced charging technologies for electric vehicles;
4. Promotion of distributed energy resources (*e.g.* domestic generation and storage.)

These are also areas in which CPS and its subsystems will catapult energy systems from silos to digitally interconnected networks; therefore, the estimated 80 billion USD costs are mainly attributable to CPS. Hereafter some distinct areas of impact, for which reliable data is available, will be addressed: Firstly, *ad-hoc* calculations of emissions and costs savings for the representative examples outlined in Section 3 will be presented. Secondly, representative examples for the literature are examined to quantify the benefits of intelligent CPS.

Illustrative Calculations:

1. **Data centres:** The energy consumption of global data centres is forecasted to grow to 3000 TWh by 2025 [83]. Since DeepMinds technology has the proven potential to reduce energy consumption of servers and data centres by 30% [57], 900 TWh of electricity generation could be saved. Using today's electricity price and the carbon footprint of California (215 kg/MWh and 0.16 USD/kWh) [187], where most servers are located, these AI-CPS efficiency improvements would equate to an extraordinary CO_2 emission mitigation of 193 Mt as well as 144 billion USD in cost savings. Such examples clearly illustrate the environmental and economic benefits CPS can provide.

2. **Building management system:** EIA estimates that building energy use will be responsible for 30% of global energy use by 2050, which corresponds to 1000 TWh [52]. According to the analysis of California's Independent System Operator (CAISO), 10% energy savings can be achieved through implementing BMS-related energy management and demand side response techniques, enabling the potential of a 100 TWh reduction in electricity use [83]. Reducing the need for this portion of electricity results in a potential abatement of 22Mt of CO_2 (eq.) as well as a cost reduction of approximately 16 billion USD.

3. **EV charging:** The IEA's Global EV Market Outlook anticipates over 120 million EVs on the road in 2030, resulting in an overall energy demand of EV charging that accounts for 6% of global power demand (approximately 200 TWh) [30]. The analysis shows that coordinated EV charging can reduce the electricity demand by 40% [138], resulting in 80 TWh total savings. Based on current electricity prices and emission intensities, the benefits of CPS in EV charging can be quantified as 18 Mt CO_2 emission abatement and 13 billion USD saving respectively.

4. **Renewable forecasting:** Based on the projection of the EIA, energy provision by intermittent renewables (*e.g.* wind and solar) has the potential to reach 11500 TWh by 2050 [52]. Again, according to a case study by California's Independent System Operator (CAISO), a 15% increase in renewable penetration can be expected with a 10% forecast performance improvement [76], which equals to a 1725 TWh electricity generation increase. The corresponding CO_2 emission reduction potential and financial optimisation can reach 380 Mt and 276 billion USD respectively.

5. **Power system optimisation:** For the proposed integrated energy management tool – J-Park Simulator – previous studies have shown that by optimising the power and heat cogeneration system on Jurong Island Singapore, the annual power generation can be reduced from 19 TWh to 12 TWh providing a notable reduction of 63% [144]. Using Singapore's power emission intensity and electricity price (*i.e.* 431 kg/MWh and 0.12 USD/kWh) as a benchmark [92], it is estimated that 3 Mt of CO_2 emissions could be achieved while 840 million USD could be saved.

These illustrative sample calculations based on the representative cases presented within this review already show the substantial economic gains and environmental benefits stemming from the application of intelligent CPS. In addition, larger scale industry studies that gauge the impact of CPS, or indeed one of its subsystems, have been carried out and will be reviewed hereafter.

Electricity Generation and Distribution Costs: As explained in Section 3, CPS can reduce production costs of an energy system consisting of 13.5% solar power by 13.2 million USD by integrating the intermittent renewables more efficiently. Based on an overall generation cost of USD 120 million, this equates to savings in excess of 11%, illustrating the enormous potential delivered by CPS. Analogue for wind generation, we reported that a system that operates with 25% wind power, a 10% forecast improvement could result in overall annual saving of 25 million USD which translates to 20% reduction of overall costs. McKinsey & Company estimate that digitalisation across the value chain of utilities can produce staggering improvements and hence cost savings [48]. In their 2018 report, the consultancy estimates that the main cost savings originate from firstly, process automation, secondly, digital enablement and thirdly, advanced analytics, fully in accordance with our assessment. The report estimates potential savings in electricity generation alone at 11% while 26% are possible in transmission and distribution. These savings are highly significant, especially in the context of a lean industry accustomed to annual gains of 1% to 2% in real terms, at the optimum. In their practice, the consultancy has seen operators reduce their costs by 10% in medium-voltage distribution grids, 15% in high- and medium-voltage overhead lines and underground cables, and 20% in high- and medium-voltage substations. Moreover, simultaneous to the operational improvements, asset reliability increases and asset management costs decrease, which will be addressed in the next section [48].

Energy Infrastructure and Maintenance: As outlined in Section 3, the transformational potential for digitalisation in energy stems from its ability to break down systemic boundaries, increasing flexibility and enabling enhanced systemic integration. The electricity sector is an integral part of this transformation, because of the progressive electrification of the whole energy system and the proliferation of decentralised power sources. Within this decentralisation, digitalisation is blurring the distinction between supply and demand and creating opportunities for consumers to interact directly in balancing demand and supply. The IEA estimates that by 2040, 1 billion smart households and 11 billion smart appliances could actively participate in interconnected electricity systems, which would assist in balancing demand and supply [83]. This smart demand response could provide 185 GW of system flexibility equivalent to the currently installed electricity supply capacities of Italy and Australia [83]. This additional systemic flexibility could reduce necessary investments in new electricity infrastructure by USD 270 billion or 15% while ensuring security of supply.

Moreover, digitalisation is and will be critical when integrating intermittent renewables by enabling grids to match energy demand to the variable provision of renewables. In the EU, increased storage and demand response could reduce the curtailment of solar photovoltaic (PV) and wind power from 7% to 1.6% in 2040, and avoid about 30 Mt of CO_2 emissions by 2040. The roll-out of coordinated charging for EVs, which minimises peak demand and assists in balancing supply and demand, could save between USD 100 billion and USD 280 billion (depending on EV uptake) by superseding investment in electricity infrastructure between 2016 and 2040 [83]. As outlined in Section 3.2, in Germany the impact would be highest as the potential for demand side management for its energy intensive industries could reach 1230 MW or 12% by 2020 [132]. However, not only investments into new infrastructure will be affected by CPS and its subsystems; the lifespan and management costs will be positively affected. Again, McKinsey & Company in their 2018 study on digitising utilities estimate that asset management costs can be reduced by up to 20% [48]. Furthermore, digital infrastructure can facilitate larger shares of distributed energy resources, turning consumers into so-called prosumers, while novel instruments such as blockchain may facilitate such local energy trading systems as discussed in Section 3.3. From these examples, it can clearly be deducted that CPS already has an impact on the evolution of energy systems and will therefore impact the design of next-generation energy architecture.

Trade-Off Between Energetic Costs and Benefits: The energy savings potential of CPS obviously goes hand-in-hand with energy utilised by the system and net energy savings have to be assessed to gauge the overall impact. Thiede studied a cyber-physical production system called EnyFlow that monitors energy demand data. It collects this data with a resolution of 1 second for machinery (10 W, 220 days per year) while utilising a desktop computer (150 W, 8760 hours per year) and tablet as well as several sensors. Introducing EnyFlow increases the energy invested by 7.7% while reducing energy needs by 20%, leading to a net improvement of 12.6%. The economic break-even, *i.e.* the return on investment, for EnyFlow is achieved within the first year, according to Thiede [173].

As decision support for assessing CPS, feasibility diagrams are essential. Based on the EnyFlow case, Figure 17 shows favourable and non-favourable areas for CPS based on the absolute potential (in kWh) that is addressed combined with necessary relative improvement impact over a defined time frame. The isopleths mark the break-even line. With that, for a given production situation (with its potential) necessary relative improvements to achieve a break-even in a given time frame can be derived. This example clearly illustrates that CPS can provide economic and environmental benefits.

Feasibility diagrams of this kind have to be developed for larger CPS in order to ensure that cost and benefits, environmental as well as economic, are balanced and that CPS provide true benefits. Since the transitions outlined above have an impact on energy economics and investments as well as the emission-abatement potential, they notably alter the marginal abatement cost curve (MAAC), *vide infra*.

Impact on Marginal Abatement Costs: In 2007, McKinsey & Company published the MACC, a curve that illustrates both the marginal cost of abatement as well as the abatement potential of certain technologies. The emergence of CPS technologies has altered

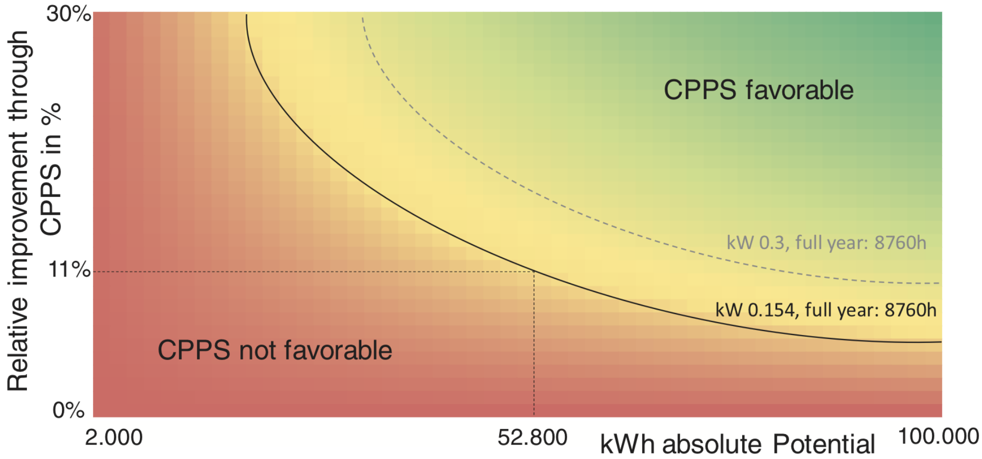


Figure 17: *CPS environmental feasibility diagram based on EnyFlow [173].*

both the abatement potential and the economics of selected decarbonisation technologies, because CPS improve efficiency, reduce risks and optimise overall processes. Figure 18 shows a simplified version of the original MACC with each technology characterised its the abatement potential and cost (top), the impact of CPS on the MACC resulting in a 20% increase in abatement potential (middle) as well as an AI-enhanced CPS version with an abatement potential increased by an additional 30% (bottom) [180]. In the baseline scenario, the marginal abatement potential and cost of selected sectors by 2030 (including building, petrochemical, iron and steel, solar, wind, coal CCS, BECCS and hybrid/electric vehicle as shown in the legend in Figure 18) are taken from the original publication. The aggregated CO_2 mitigation potential from these sectors is estimated at 7.7 Gt [94, 116, 172].

In the CPS scenario, aforementioned CPS technologies are assumed to be applied, leading to significant increases in abatement potential as well as reductions in cost as noted by transparent areas in the middle of Figure 18. From the survey outlined above it can be concluded that state-of-the-art CPS technologies will continue to be integrated in different sectors in the coming years and the delivery of economic and environmental benefits is highly likely. Moreover, future developments of CPS technologies, such as the combination of AI with CPS, are estimated (bottom in Figure 18). Based on the analysis presented herein, it is estimated that by integrating both current CPS technologies and future CPS technologies into the investigated sectors, the CO_2 abatement potential could be increased from 7.7 Gt to 9.4 Gt (a 20% increase) and 12.2 Gt (another 30% increase) respectively. In particular, the largest increase comes from the hybrid/electric vehicle sector, building sector, and solar and wind generation, whereby the CO_2 abatement potential could increase by 40%, 28% and 20% respectively.

It has to be noted that the impact of CPS technologies on renewables and electric vehicles critically depends on the penetration level of renewables in the energy system as well as the percentage of electric vehicles in the overall fleet. In this paper, predictions for these factors are adopted from references [50, 86]. Consequently, the calculations presented herein are critically dependent on the accuracy of the forecasts cited. Moreover, the ap-

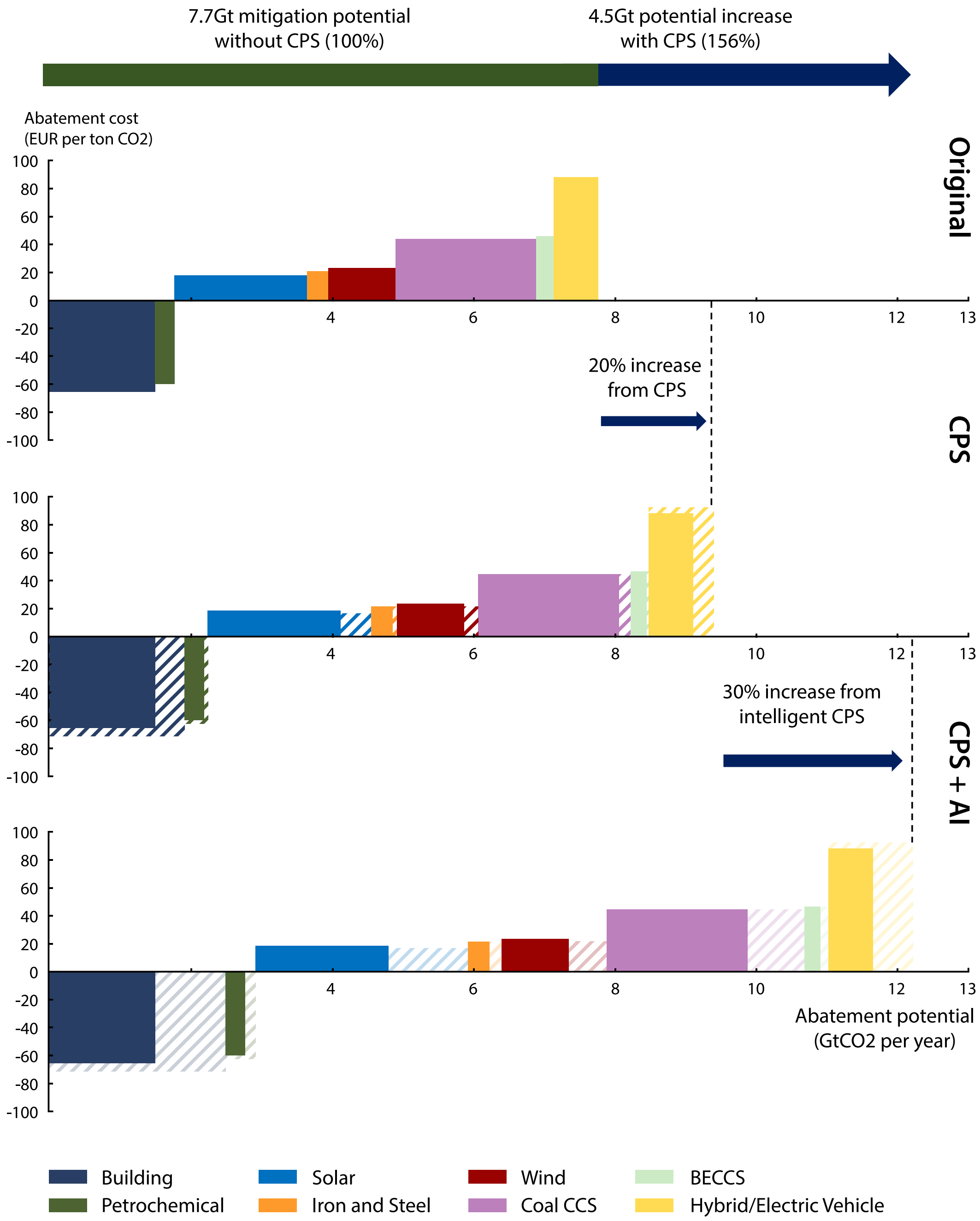


Figure 18: *Impact of CPS technologies on the marginal abatement cost of selected decarbonisation technologies in energy transition. Shown in the figure is the marginal abatement cost of selected decarbonisation technologies (represented by different colours) without CPS technologies (top), with CPS technologies (middle) and with intelligent CPS technologies (below).*

plication of CPS technologies in the investigated sectors could reduce the abatement cost of such decarbonisation technologies, especially in sectors which already have significant ICT infrastructures. According to our estimations, CPS technologies could reduce abatement costs in most sectors by 5%-15% without any additional investment (transparent areas in Figure 18).

While the estimates used for the establishment of the revised MACCs displayed in Figure 18 are subject to distinct uncertainties, the economic assessment of CPS technologies combined with the abatement potential speaks for itself: CPS, especially when combined with AI, can catapult us onto unforeseeable decarbonisation pathways while saving money. In order to meet emission targets and restrict the increase of global average temperatures to 1.5 °C, intelligent CPS are indispensable. However, the application of these systems also comes with some drawbacks, which will be discussed in the subsequent section.

4.2 Energy security implications

Cyber-Threats to Energy and Industrial Security: The enormous benefits outlined in Section 4.1 come with distinct downsides: while CPS will enhance the operations of critically important sectors such as energy and industry, it will simultaneously make them more vulnerable to cyberattacks and thereby cyber-dependent [188]. Hostile entities could severely affect national economies by disrupting the strategically important supply of energy at any point across the energy value chain. Due to the inherent nature of CPS, which connect the cybersphere with the physical world, attacks can penetrate from one to the other, thereby creating significant risk in the real world. CPS are consequently not only the enabler of efficiency improvements, increased resilience and heightened safety, but simultaneously exacerbate the consequences of a potential cyber-threat [133]. For instance, industrial control systems (ICS) could be disabled which would lead to loss of control of critical infrastructure and hence could cause a dangerous failure of a critical energy asset. Moreover, a cyber-attack could open a safety valve or redefine security settings, creating significant risks to humans in the physical world. Cyber-attacks on the energy sector are therefore a severe threat to public safety and economic security [33]. Consequently, this new form of crime creates new risks and vulnerabilities, particularly for the stable functioning of Critical Infrastructures and ICS as well as integrated and digitalised supply chains. To make matters worse, cyber-attacks have become both more sophisticated and more frequent. Hereafter, we will briefly review the economic impact and countermeasures as well as the role of governments in mitigating cyber-threats.

The Economic Impact of Cyber-Crime: Even though political and public consensus has been building on the importance of cyber-security in general, and especially for energy provision and industrial production, efforts by industry to strengthen its cyber-defense capabilities are not deemed to be sufficient [45]. Estimations put the economic damage from cyber-crime for global businesses at 450 billion USD [62]. For example, a cyber-attack on the distributed energy resource management system could result in damage to transformers, which are expensive and often difficult to replace [33]. Therefore, industrial production and energy provision have been the main targets of cyber-attacks with 33% and 16% respectively. Accenture and the Ponemon Institute estimate that the average levelised cost for the energy and utilities sector amounts to 17.2 million USD [136].

The insurance market Lloyd's of London estimates that an extremely disruptive cyberattack could cause up to 120 billion USD of economic damage, exceeding that of major natural catastrophes [100]. It is therefore of paramount importance that industrial-scale operating systems are equipped with built-in security measures that exhibit several layers of protection as opposed to an external security wall. While such multi-layer systems are being implemented, progress is rather slow. The economic ramifications of cyber-attacks therefore justify significant investments in cyber-security measures, an important topic that will be outlined in the subsequent section.

Cyber-Security and Resilience: Until recently, cyber-resilience mainly focused on hardening the perimeter around cyber-systems, but these measures are not always the most cost-effective ways to reduce the impact of cyber-crime. Accenture proposes a three-step process in order to shield CPS from cyber-attacks and thereby prevent real-world damage [136]. According to expert analysis, higher-value assets, *i.e.* the assets critical for operation and security, must be shielded using several, hardened perimeters. The rational behind this is to make it difficult, expensive and time-consuming for attackers to achieve their goals. Apart from the focus on critical assets, three maxims are proposed:

1. Strong foundation: security intelligence as well as advanced access control are the foundation of an intelligent cyber-security system;
2. Pressure testing: testing using outside agents is key to verify the protection of critical assets and furthermore, locate other vulnerabilities of the CPS;
3. Invest in next-generation technology: AI and advanced analytics will, over the coming decade, assist with both protection from and detection of cyber-attacks. Investments in this area are needed to protect CPS from the next generation of cyber-attacks.

In a recent review article addressing the challenges of securing CPS, Cardenas et al. dive into the specific of safeguarding [28]. Therein, the authors argue that patching and frequent updates are not well suited countermeasures for CPS-based control systems as these systems monitor industrial processes in real-time and therefore cannot easily be taken offline and upgraded. Better preventive measures are redundancy and diversity to minimise the damage from one affected entity, the principle of least privilege that limits the amount of duties one entity has and the utilisation of game theory to play through realistic attack scenarios.

Over the last 10 years, security information and event management (SIEM) software has received much attention from corporates as a means to efficiently manage cyber-threats and attacks. SIEM technology initially evolved from log-management, *i.e.* the monitoring of agents logging in to a cyber-system. SIEM software collects and aggregates log data generated by the cyber-system's technology infrastructure, from host systems and applications to network and security devices such as firewalls and antivirus filters. The software then identifies, categorises events/incidents and analyses them. Thereby, the software fulfills two main objectives: firstly, it reports on security-related incidents, such as successful and failed logins, malware activity or other potentially malicious activities.

Secondly, it uses the analysis to report on potentially malicious activities. It is therefore a mechanism that helps companies to mitigate cyber-attacks at a point when they have already managed to circumvent the perimeter and penetrate the system [18, 21, 174]. It can therefore be concluded that there are many efficient ways to safeguard CPS and increase their cyber-resilience, but their effectiveness can only be tested when they are applied in the real world. Yet another difficulty arises when the threat actually comes from within the CPS. an issue that will be addressed henceforth.

Making CPS Intelligent: Yet another issue stems from the fact that AI carries intrinsic risk ranging from risks for human employment to existential risk for humanity. An example of existential risk posed by intelligent CPS and fiercely discussed at present is the issue surrounding the crashes of two of Boeing's 737 Max aeroplanes. Due to incorrect data from a faulty sensor which indicated that the airplane was stalling, an automated system known as the maneuvering characteristics augmentation system was initiated, incorrectly pointing the aircrafts nose down to prevent stalling. In both accidents, involving an Indonesian and an Ethiopian carrier, the pilots did not manage to overrule the machine's actions, resulting in the death of several hundred people. It is far beyond the scope of this review article to address the general ethical and philosophical concerns regarding AI and the interested reader is therefore referred to books by Barrat [15], Harrari [72], Bostrom [24], Tegmark [171] and Kurzweil [103]. It is without the scope of this article, however, to discuss which safeguards CPS could provide and which override mechanisms could be implemented to prevent tragedies like these two aircraft crashes.

From this section, it can be concluded that CPS will provide real advantages in terms of sustainability and economics in many areas while introducing completely new risks. In order to safeguard against these risks, policy makers must have the foresight to implement policies aimed at alleviating them; several important proposals will now be outlined.

4.3 Policy implications

The rapid developments of digital technology combined with the falling costs outlined in this review article are driving the digitalisation of energy systems and industrial production. However, efficient policy and market design are critical to help steer this transformation onto a secure and sustainable path. Many governments have developed holistic policy packages to support CPS, for example in Industry 4.0, as implementing the mechanisms of advanced manufacturing and efficient energy provision is seen as a clear competitive advantage. Missing out on this advantage would cost economies significantly and therefore, many governments have decided to support digitalisation efforts as well as their safeguarding using public funds.

Supporting Cyber-Physical Systems: Governments understand that the economic competitiveness of their respective countries critically depends on the efficient implementation of digital technologies, *i.e.* CPS and its subsystems, in advanced manufacturing and low-carbon energy provision. The European Union, for instance, has established complete frameworks that put in place policies and supporting funding for developing pilots, education or research in digital manufacturing. These policy levers are mainly targeted at SMEs to ensure that this segment can participate in and benefit from the advantages provided by CPS. A comprehensive overview of the EU's initiatives as well as the endeavours of its member countries are provided in [56]. Singapore's Industry 4.0 initiative is outlined in [46], while the US's "Revitalising American Manufacturing" can be found in [122]. Figure 19 gives a visual overview of the policy landscape in the EU, at present the leading region with regard to advanced manufacturing and digital energy. It can be seen from the third column of Figure 19 that investments are substantial; for instance, the largest public investor in this sphere is France, who has committed approximately 10 billion EUR to reinvigorate its manufacturing base after experiencing fierce industrialisation over the past decade. Germany, the EU's industrial powerhouse, has committed much less but has invested very early in order to remain one of the world's top industrial producers. In the German case, investments are directed to CPS rather than Industry 4.0 (Figure 19, rightmost column) illustrating that although initially an industrial topic, CPS are deemed relevant in other economic sectors as well.

	Launch date	Target audience	Budget	Funding approach	Strategic focus	Technology focus
	2015	Industry & production base, SME & mid-caps	10 billion EUR	Mixed	Deployment	Transportation, IoT, artificial intelligence, Big data, HPC, Digital trust, healthcare, smart cities
	2011	Manufactures/producers, SME & policy-makers	200 million EUR	Mixed	Deployment	Cyber-physical systems, IoT
	2012	Large companies, SME, university, research centers	45 million EUR	Public	R&D	Generic
	2014	General business community	25 million EUR	Mixed	Deployment	Generic
	2016	Industry, SME & micro-enterprises	97.5 million EUR	Public	Mixed	Digital platforms, Big data, collaborative applications
	2013	Research, academic & SME	50 million EUR	Mixed	Deployment	Generic
	2012	Business, industry & research communities	164 million EUR	Mixed	Deployment	Aerospace, automotive, chemicals, nuclear, pharma, electronics
	2016	Industry & service sector companies, trade union	Not yet defined	Public	Deployment	Generic

Figure 19: *Overview over targeted policy framework that foster Industry 4.0 as well as the implementation of cyber-physical systems [56].*

Due to the pronounced impact that CPS will have, and the large investments committed, the authors conclude that implementing CPS will be crucial for economic survival, especially for advanced economies. However, simultaneous to fostering investments in CPS and its development, policy makers are concerned with the impacts of these systems on environmental sustainability and national security, two dimensions of CPS that will be addressed briefly in the following paragraphs.

Environmental Policy: CPS have already been applied to monitor many environmental processes ranging from water supply to fire detection. Policy makers should incentivise the use of CPS in order to accelerate their uptake in environmental protection. Such incentives could range from direct support or to tax schemes favouring secure CPS technologies that provide environmental benefits. Moreover, regulations could be adapted, for instance a tightening of energy standards for appliances and machinery that can only be met when monitored and optimised in the cyber-realm. In any case, more and more regions have internalised emissions in energy prices using carbon pricing or taxes and consequently, economic incentives to use CPS to optimise operations are already in place, though indirectly.

Security Policy: Just as in the case of environmental concerns, private sector players already have clear incentives to safeguard their CPS as attacks can be enormously costly (see above). Since industrial production and energy security are matters of national security, policy makers have to ensure that security standards are implemented to safeguard economic output and hence society as a whole. The U.S. Department of Homeland Security, for instance, has initiated the cyber-physical systems security (CPSSEC) task force. CPSSEC engages through a combination of coordination with the appropriate sector-specific oversight agency, government research agencies, industry engagement and support for sector-focused innovation, small business efforts and technology transition. This work encompasses the development of sector-specific industry consortia tasked with monitoring and improving the security and resilience of CPS [43]. Germany has initiated a similar endeavour, the cyber-security strategy, part of the Federal Office of Security in Information Technology [27]. This cyber-security strategy contains a range of policy levers that are aimed at increasing security and safeguarding the German economy. While these are two prominent examples of leading economies, most OECD countries have holistic policy packages implemented to protect industry, citizens and their national interest from cyber-attacks. A comprehensive comparison can be found here [128].

In addition to these direct threats, policy makers are aware of the issue of data protection for consumers and businesses and have proposed solutions that safeguard data protection and IT security, minimising economic vulnerability in this regard. The EU's general data protection regulation (GDPR) is already tackling privacy and security issues that arise from the implementation of CPS in various walks of life.

Governing Artificial Intelligence: Nick Bostrom argues that sufficiently intelligent machines could improve their own capabilities faster than human computer scientists and therefore the outcome could be an existential catastrophe for humans [24]. Since CPS bridge the cyber-world in which AI exists with the real, physical world, they are the enablers of AI's direct impact on the world and hence human lives [171]. Via CPS, superintelligence could affect our life in the physical world and consequently marginalise humankind. It is therefore of utmost importance and urgency to regulate AI appropriately in order to avoid such an existential risk. While there are clear proposals for regulating AI, the regulation of AI-enhanced CPS is in its very early stages. Respecting data privacy has to be implemented into AI algorithms to balance functionality and data privacy, *i.e.* AI should be most effective while respecting people's privacy. While the EU's GDPR has made tremendous progress in this realm, combining CPS with AI will be the next hurdle for smart policy design.

Yet another important area is transparency; the operations of AI have to be fully transparent so that the chain of reasoning leading to a decision is fully comprehensible. This is critical, for example when investigating the negative effects caused by a decision made by an AI-like algorithm. Fairness as well as ethics of machine decisions have to be accounted for, a formidable problem not only to be solved by policy makers, but also philosophers.

It is anticipated that AI in the medium-term will be equivalent to human intelligence, so-called human-like machine intelligence, and will also have the ability to surpass it in the long-term, so-called super-intelligence. Such advanced AI has to be guided by governing principles, equivalent to Asimov's Laws of Robotics, that ensure that AI works to promote the wellbeing and prosperity of humankind as a whole while protecting individual human rights and fostering democracy. This issue will be addressed in a forthcoming publication [80]. It can be concluded that policy makers are well aware of the issues surrounding CPS and that policy frameworks are in place that foster the development of CPS, safeguard them and direct them onto a sustainable pathway. The critical gap is the implementation of AI into CPS, so-called intelligent CPS; here, policy makers have to act with foresight to preempt possible detrimental impacts on economies and people.

From the analysis of the advanced marginal abatement cost curve as well as policies of leading economies in this race, it can be concluded that the risk CPS pose is well worth taking and the benefits of CPS clearly outweigh the risk for cyber-security, given the right measures are adopted.

5 Conclusions

In this comprehensive review article, the impact of so-called cyber-physical systems (CPS) as well as their subsystems on the decarbonisation of energy was assessed. CPS are defined as high-level orchestrations of various cutting-edge digital technologies creating a digital representation of the physical world. This digital representation enables the advanced operation and control of the physical system using advanced optimisation tools as well as novel digital technologies. Among these technologies are big data, machine learning, IoT, AMI, blockchain and the semantic web. This orchestration will lead to synergetic benefits in terms of economic improvements and environmental sustainability that go way beyond the potential of isolated digital technologies.

The envisioned transition of energy systems towards sustainability has three critical dimensions relevant for its success: (i) low-carbon power provisions, (ii) energy efficiency improvements and (iii) energy storage adoption. This article gives clear examples showing that CPS technologies will be critical for the successful implementation of all three dimensions. First examples of the implementation of AI into CPS have shown that this synergetic combination can have unanticipated benefits and will lead inevitably to economic and environmental gains, but may lead to societal risks that are unforeseeable at the time of writing.

Case studies were used to illustrate the benefits of CPS and its sub-systems for the economic and environmental viability of the main pathways to the low-carbon energy systems named above. In case of renewables, CPS will promote the integration of the intermittent energy source in existing energy system, e.g. through computer-aided renewable resources identification and renewable energy forecasts improved by machine learning technology. In the case of energy efficiency, CPS are having an impact that is highly likely to increase significantly over the coming years; this effect is exemplified using advanced building management systems, the optimisation of data centres and enhanced demand side management. Last but not least, CPS will be critical for facilitating energy storage especially when considering cross-sector power-to-X. This effect is illustrated using CPS-enhanced smart charging of electric vehicles and blockchain-enabled P2P energy trading.

These case studies illustrate that intelligent CPS will not only be beneficial for economic optimisation, but will deliver environmental advantages like emission abatement and simultaneously increase energy security. Ad hoc calculations of the monetary benefits and emission savings potential illustrate and prove this point. CPS are already having an impact on CO_2 emissions and the economic viability of industry; it was shown that even in sectors that are used to improvements in the single digit percentages, CPS can enable improvements of 30% and beyond while advances in artificial intelligence will likely drive improvements even further over coming decades. A clear illustration of the cumulative benefits of intelligent CPS is given in the revamped MACC curve – abatement potential can be improved by 56% while costs can be reduced by more than 30%.

This assessment also clearly shows that supporting CPS in the field of energy provision is also an obvious climate change mitigation strategy. Governments should support CPS that drive energy efficiency as part of their decarbonisation strategies; from a cost-benefit perspective CPS deliver emission savings at a cost far below that of traditional mitigation strategies. Policy makers should consider incentives for CPS that optimise not only energy provision, but also industrial production and transport.

All these benefits have clear downsides. While beneficial for energy security, CPS are connecting cyber-threats with the real, physical world and therefore cyber-crime could have more direct impact. Policy makers have to continuously review CPS and AI in order to foster benefits and safeguard risks; policies for this have to be adapted in a cycle much shorter than the current one. Moreover, governance of artificial intelligence is a most pressing issue: it has to be regulated as AI connected to CPS creates a *deus ex machina* with unforeseeable consequences and thinkers from the realm of ethics, philosophy, law and computer science have to devise ways to ensure that AI and intelligent CPS are serving humanity.

6 Outlook

It was shown that CPS are already having an impact in the realm of energy provision while there are indeed teething issues. The impact of CPS will likely increase in the short-term and centainly will affect energy provision & industrial production in the long-term. The actual impact will depend on the real-world adoption of novel technologies, such as electric vehicles, renewables and distributed storage, but in any case will be significant. Artificial intelligence will further add to the impact of CPS, and the pace of development of AI and its ultimate scale are not currently foreseeable, posing a significant challenge to policy makers. Due to the uncertain but potentially enormous impact, governance of intelligent CPS is critical and policy makers have to act. Owing to the uncertainty, developments in CPS and AI are difficult to forecast and this area must therefore be monitored continuously.

It is also clear that intelligent CPS will not only affect industrial production and energy provision, but will significantly accelerate scientific research and technological developments, making long-term predictions even more difficult than before. In the short-term, however, these systems are likely to demand significant amounts of electricity and precious resources. Nevertheless, intelligent CPS have the possibility of finding pathways that can help humankind to meet the ambitious decarbonisation and emissions targets that are at present deemed unreasonable and unattainable. Therefore, intelligent CPS may have the potential to "save the planet".

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