Control for smart systems: Challenges and trends in smart cities

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Abstract: There have been tremendous developments in theories and technologies in control for smart systems. In this paper we review applications to various systems that are crucial for the future of smart cities, for example enterprise and manufacturing systems, transportation systems, energy systems, and data centres. Beyond discussing the existing technological trends and the methodological approaches developed so far for managing and controlling such systems, we also provide visions on the future challenges for these systems in these various aspects.

1. Introduction

It is well known that cities around the world are expanding dramatically. To counteract negative effects of this expansion and make the city more liveable, smart solutions are becoming more and more crucial in different sectors.

Due to the limit of space in this work and the expertise of the authors, we focus on four systems in smart cities, namely enterprise and manufacturing systems, transportation systems, energy systems, and data centres. This list is by no means complete. Many other important systems in smart cities are unfortunately not included in this work, such as water system, public health system, and financial system, etc. We wish the discussion may benefit these other systems, too.

Enterprises and manufacturing companies operating in the cities have impact on the traffic, energy consumption, pollution but also on the social sustainability by providing work. Transportation systems with the associated pollution and negative impact on the life of commuters are a key challenge. Energy systems in general and energyhungry data centres in particular are an increasingly relevant aspect that needs to be handled by smart cities.

A smart city will be able to apply new technologies and innovations in an interoperable and integrated fashion, to achieve benefits for its inhabitants, in terms of environmental impact reduction, inclusiveness and integration among the communities, fight against energy poverty and water scarcity. In other words, a smart city will contribute towards a sustainable way of living for all its citizens. In this context, the optimisation and control research community has a crucial role in the development of models and algorithms for the design, implementation and operation of smart solutions for cities of the future.

Note that the term ‘‘smart’’ and ‘‘intelligent’’ have been co-existing for a while, though their relationship and difference have been vague. There is a trend to use ‘‘smart’’ to describe systems involving human operators and to use ‘‘intelligent’’ to emphasise more on the situation awareness as well as self-X capabilities (such as self-intelligence) of

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systems themselves. However, such a difference is field dependent and has to gain wider acceptance. Therefore in the rest of this article, we do not emphasise differences between ‘‘smart’’ and ‘‘intelligent’’ and use both terms interchangeably unless stated otherwise.

The rest of this article is organised as follows. We discuss smart enterprise and manufacturing systems in Section 2, smart transportation and mobility systems in Section 3, smart energy systems in Section 4, smart data centres in Section 5, and briefly conclude in Section 6. We hope that this article brings insight to this field.

2. Smart enterprise and manufacturing systems

The industrial sector will change more in the next 5 years than it has in the last 15. From digital twins to predictive maintenance, to cobots, Industrial Internet Of Things, 5G or cybersecurity, the factory is changing. Meeting the environmental challenge is an emergency for society and manufacturing companies alike. Greener, more sustainable, and more transparent industries must take up the issue for having a positive impact to the cities. The enterprise is changing as a whole and, in the era of the smart city, workspaces are being reorganised. Managerial innovation, agility, collaboration and learning organisation are the major pillars to make the manufacturing enterprises smarter. Smart enterprise and manufacturing will contribute heavily to the challenges and trends for smart cities.

The rise of the new industrial revolution, known as ‘‘Industry 4.0’’ (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014), allows enterprises and governments to adopt and develop new technologies in order to develop new products, shorten development periods, achieve resource efficiency, or provide more personalised products (Romero & Barafort, 2020). It is based on the IT-driven transformation of manufacturing systems (Lasi et al., 2014), grounded in concepts such as cyber–physical systems (CPSs), Internet of things (IoT), decentralised decision-making, individualisation of products, and services (Rojko, 2017). The evolution from product to service-oriented enterprises is a factor that plays an important role in this trend (Luigi Atzori & Morabito, 2010). Terms ‘‘Smart Industry’’, ‘‘Smart Manufacturing’’ and ‘‘Industry 4.0’’ are used interchangeably (Muhuri, Shukla, & Abraham, 2019).

A relevant aspect in this new scenario is the focus on the reduction of gap between physical and cyber components, accomplished through the integration of operation systems and Information and Communication Technologies (ICT) with the vision of forming CPSs (Dalenogare, Benitez, Ayala, & Frank, 2018; Georg Weichhart & Molina, 2021). Moreover, there is a trend towards moving from the development and application of computer-aided approaches (Chang & Wysk, 1997; Raphael & Smith, 2003; Sholom M Weiss & Safir, 1978) to more digital, networked, and intelligent methods e.g. building on agent technology (Chang & Wysk, 1997; Leitão et al., 2018; Sholom M Weiss & Safir, 1978; Valckenaers, 2019). Within this context, the concepts of Smartness and Smart Systems have begun to be used in many domains. The term ‘‘smart’’ has been widely used to name products (Smart Phone, Smart TV, Smart Watch, etc.) as well as methods, applications, frameworks, and techniques proposed in the scientific literature (Cangussu, Cooper, & Li, 2004; Crow, van Den Berg, Huffman, & Pellarin, 2011; da Silva, Salles, & Prates, 2010; Dong & Kamat, 2010; Wang & Chen, 2011; Zeinalipour-Yazti, Laoudias, Andreou, & Gunopulos, 2011). Recently, concepts such as Smart Cities (Koutra, Becue, & Ioakimidis, 2019), Smart Manufacturing (Kang et al., 2016; Kusiak, 2018), or Smart Grids (Lovell, 2018) have gained attention not only being tackled by industry practitioners but also being widely discussed in the scientific literature. Generally, these concepts are associated with advances in specific fields through the development, implementation, and application of ICT (Blau, Kramer, Conte, & Van Dinther, 2009), the use of intelligent devices (El Hendy, Miniaoui, & Fakhry, 2015), or Artificial Intelligence (AI) methods (Wolter & Kirsch, 2017), and novel industrial and management technologies (Lim & Maglio, 2018).

Smart Industry or Smart Enterprises are defined by the ideas of Smart Factories, which are flexible Cyber–Physical Production Systems (CPPS) (Georg Weichhart & Molina, 2021; Hervé Panetto & Macchi, 2021) that provide personalised services or products to customers, and their functioning is based on the use of Big Data (Romero et al., 2020). In this context, the Smart Enterprise is an evolving network of Smart Factories that fosters and is influenced by the participation of researchers, developers, suppliers, distributors, and end users (Vyshnevs’kyi & Knyazev, 2017). Moreover, it is possible through a synergy of IoT devices that allow to enhance the use of computers in the enterprise (Kaur & Sood, 2015). In a broader way, Smart Service System and Smart Enterprise are systems composed of people, information, organisations (Romero, Guédria, Panetto, & Barafort, 2022), and technologies that interact towards the achievement of common objectives (Maglio, Vargo, Caswell, & Spohrer, 2009). They depend not only on the system elements by themselves but also on the manner in which those elements interact. They are also able to learn, perform dynamic adaptation, and make decisions considering data that is received, transmitted, or processed to improve their capabilities in the future. This type of service system puts special emphasis on the human, so that aspects such as knowledge, capabilities, and value are defined by the people of the system (Maglio, Kwan, & Spohrer, 2015). The expectation for the future of manufacturing is a transition towards Smart Factories built on CPPS. This trend is outlining the emergence of various characteristics forming the essence of Smart Manufacturing (Barari, de Sales Guerra Tsuzuki, Cohen, & Macchi, 2021; Ghobakhloo, 2018; Kusiak, 2018; Monostori et al., 2016; Napoleone, Macchi, & Pozzetti, 2020; Tao, Qi, Liu, & Kusiak, 2018). • Manufacturing systems are increasingly dependent on data. New IoT devices, new sensing capabilities and edge computing platforms are introduced (Kusiak, 2018). Technologies are evolving and retrofitting existent factories, to transform them into smart ones, is an essential task. Smart features aim at exploitation of big data, by means of the integration of new data sources with more traditional data sources (Zdravković, Panetto, & Weichhart, 2022), such as Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), Supervisory Control and Data Acquisition (SCADA) and Programmable Logic Controllers (PLCs), where large volumes of management and process data are available (VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik, 2013).

- Data-driven modelling is gaining momentum as key resource for the management of operations (Tao, Qi et al., 2018). CPPSs are enabling manufacturing enterprises to gather more insights from the shop-floor and provide a basis for robust decision-making in the planning and control cycle (Negri, Pandhare, Cattaneo, Singh, Macchi, & Lee, 2021; Tao, Qi et al., 2018). In this scenario, dynamic predictive and optimisation models are becoming cornerstones, synchronised with the field through monitoring capabilities while aiming to absorb the effects of variability on the production performances.

- The variety of products is ever growing and enables the enterprises to dynamically fulfil their customers' needs. The use of new manufacturing technologies, processes and materials is a key factor to this end. Additive manufacturing is a clear example of a new manufacturing technology (Kusiak, 2018) that allowed to adopt new materials, had impact on the design and manufacturing of products, and created opportunities to move even towards a personalised production. Additive manufacturing is a paradigm change, where materials are added to form a solid product (part) in a step, by step manner. In contrast to this, today's approaches are cutting of materials, e.g. when a car's engine block is first casted and then the cylinder bore is cut into the engine block. The excess material is hardly recycled. Therefore, the adoption of additive manufacturing would provide opportunities for smart cities to efficiently use materials and to reduce waste and pollution. Besides additive manufacturing, responsiveness to the market requirements can leverage on robotics in manufacturing systems (Ghobakhloo, 2018; Wang, Ma, Yang, & Wang, 2017), with a particular interest on the human–robot collaborative workplaces and flexible intralogistics (Fragapane, Ivanov, Peron, Sgarbossa, & Strandhagen, 2022; Simões, Pinto, Santos, Pinheiro, & Romero, 2022).

- The role of humans is essential in different aspects. In this context, it is worth remarking that the technologies implemented in collaborative robotic systems are requiring design and management practices that consider human factors and human-in the-loop (Cimini, Pirola, Pinto, & Cavalieri, 2020; Simões et al., 2022). The advancement of human–machine interfaces is also opening new doors to introduce non-conventional interaction modes, built upon different technology options, such as the augmented reality (AR) or AI-powered digital assistants, as intuitive aids to access information and integrate human knowledge.
- The disruptive evolution of simulation technologies such as Digital Twins is full of promises for the future (Cimino, Negri, & Fumagalli, 2019; Concetta Semeraro & Dassisti, 2021). Digital Twins are a core element in the virtual part of a CPPS, offering a synchronised mirror of a physical production asset or system to enable advanced decision support. Starting from the adoption of Digital Twins in Product Life-cycle Management, investigations are nowadays extending towards applications of Digital Twins to the manufacturing and service domain Tao, Cheng

et al. (2018). Thus, by means of Digital Twins, virtualisation will advance the design and management practices in manufacturing.

- The development of advanced control theories built on collaboration and autonomy with self-X capabilities available in the manufacturing shop-floor (self-execution, self-organisation, self-learning, self-reconfiguration, self-adaptation etc.) is expected as a key feature in CPPS (Panetto, Iung, Ivanov, Weichhart, & Wang, 2019; Tao, Qi et al., 2018). Building on self-X capabilities, CPPS can make decisions autonomously while remaining coordinated towards common organisational goals. To this end, CPPS are supposed to embed a certain level of intelligence. In particular, it is essential to consider the development of AI technology, both as a local and a global intelligence at the different levels of the factory, from machines to production networks.

- Innovative services can exploit the cyber part of physical systems. Indeed, a growing interest in new business models is evident, in order to favour the profitability of services (Thoben, Wiesner, & Wuest, 2017). In particular, the possibility to retrieve a large amount of data from connected sources is a key source for the value creation in the context of service provision. This requires enriching the theory of data-driven services, and calls for the development of data-driven product service systems leading to innovative business models that take advantage of the digital transformation (Lee, Kao, & Yang, 2014; Zambetti et al., 2021).

Overall, different capabilities are emerging in Smart Factories. The transition requires to integrate advanced technologies in the factory and CPPS are a transformative means to this end:

1. integration and interoperability of cyber–physical systems is the basis which will ease the exploitation of advanced analytics, AI technology (machine learning and reasoning), simulation and optimisation models, as core elements of management and control of manufacturing operations, and the joint optimisation of design, process planning and manufacturing execution;
2. cyber–physical integration will provide the platform where the integration of new manufacturing technologies and processes is hosted, including additive manufacturing, computer vision, collaborative robots, mobile robots, autonomous vehicles, drones, etc.

In a wider context, where manufacturing is playing an important role, are trends in sustainability and the circular economy in general (Crisostomi et al., 2020). Also highly relevant are challenges like resilience in manufacturing; these are pushing towards additional capabilities enabled by Smart Manufacturing technologies. Besides these aspects, the digital transformation in the service domain is still in its early stages towards the provision of advanced services centred around bigdata enabling new products and assets in the context of innovative business models.

3. Smart transportation and mobility systems

Mobility systems represent an essential element of smart cities. In the last decades, the transportation sector has been dominated by private vehicles, powered by combustion engines, causing congestion phenomena, air and noise pollution, problems to human health, quality of life and personal safety. All the modern cities are nowadays totally changing, towards smart mobility solutions able to improve the efficiency and environmental sustainability of cities. This can be achieved thanks to Intelligent Transportation Systems (ITS) solutions that exploit communication technologies to maintain road users safe while driving, to inform citizens about available parking spaces, delays in public transport, road accidents, to analyse crowd behaviour, to optimise routes and travel choices, to control all the transport systems for both passengers and freight. The presence of a large volume of mobility data generated by users adopting smart technologies and online social media also allow the application of AI techniques (Mahrez, Sabir, Badidi, Saad, & Sadik, 2021).

As discussed in Lyons (2018), a smart urban mobility system exploits technology to generate and share information to influence the users' decisions, to enhance vehicles, infrastructure and services, and, more in general, to derive improvements for all the operators, users and stakeholders. Another very important aspect is the strong connection of smart mobility with sustainability issues, which leads to a definition of smart urban mobility as the connectivity of people, goods, services, and opportunities that is affordable, effective, attractive and sustainable (Lyons, 2018). It is then clear that the development of new control methods and algorithms is absolutely essential for the advancement of smart city mobility initiatives. There are many challenges, related to data collection and processing, dynamic resource allocation, data-driven optimisation, and control, that the systems and control research community must face to transform the smart city vision into a reality (Cassandras, 2016).

Smart mobility systems can be designed following different aspects, which are addressed in the following subsections.

3.1. *Autonomous driving*

One of the most disruptive innovations in smart mobility systems is represented by the transition towards Connected and Automated Vehicles (CAVs), which could help improve road safety, energy efficiency, urban accessibility and social inclusion.

Autonomous driving systems are built upon a modular pipeline consisting of perception, localisation, decision making and motion planning. An interesting survey on motion planning and control techniques for self-driving vehicles in urban contexts can be found in Paden, Čáp, Yong, Yershov, and Frazzoli (2016). In the motion planning task, agents are typically concerned with realising primarily a global behaviour. Collision avoidance and other safety considerations are then added as secondary objectives, resulting in a hierarchical composition of multiple objectives. The trade-off between performance and safety has raised widespread discussion in recent years (Shalev-Shwartz, Shammah, & Shashua, 2016).

The control and optimisation of autonomous driving has great potential on smart cities to relieve the energy consumption and transportation congestion. However, it remains challenging to find promising sample sequence in uncertain environments with safety concerns. Such safety-critical problems can be divided into three categories: state constraints with high confidence (Fisac et al., 2018), risk-sensitivity depicted by variance (Chow, Tamar, Mannor, & Pavone, 2015), and temporal logic related to sequential restrictions (Hasanbeig et al., 2019).

To address safety verification of dynamic systems, Control Barrier Function (CBF) is often used (Wang, Ames, & Egerstedt, 2017). Conceptually, it may ensure the safe property of systems without explicitly calculating the forward reachable set (Prajna, Jadbabaie, & Pappas, 2007), which provides a formalism to define and evaluate the safety in motion planning tasks. However, the system dynamics is not always known in practice, which means that a nominal model is not accurate enough at some point. There are some existing works to extend the use of CBFs to systems with unknown dynamics (Robey, Lindemann, Tu, & Matni, 2021; Taylor, Singletary, Yue, & Ames, 2020). But the problem in general still remains open.

As an efficient tool to deal with end-to-end navigation, the framework of reinforcement learning (RL) can be applied to configure unseen patterns by encoding observation to retain a target control without too much prior knowledge. Thus, safe RL has great potential to conclude a model-free policy that could provide exploration for unknown system dynamics (Garcıa & Fernández, 2015). Combined with classic control techniques like formal methods (Alshiekh et al., 2018) and Model Predictive Control (MPC) (Zanon & Gros, 2020), safe policy is synthesised with theoretical guarantees. To maintain the property of forward invariance in a safe set, CBF provides a manner to obtain provably and scalable collision-free behaviours. The ordinary integration of CBF and RL could compensate for the shortage of exploration efficiency and obtain safety with high probability (Cheng, Orosz, Murray, & Burdick, 2019). Safe RL shows great potential to obtain safety with high probability, and it remains further study to measure the uncertainty in a more robust way.

3.2. *Traffic control*

Smart mobility in the urban environment can be enhanced by applying traffic control schemes in order to manage and regulate the traffic flow efficiently, i.e. by minimising travel times, by maximising the system throughput, by minimising emissions, just to mention a few of the most common cost functions. This can be achieved by optimally coordinating the traffic signals in the urban network, as for instance in Jamshidnejad, Papamichail, Papageorgiou, and

De Schutter (2018), in which MPC strategies are developed and gradient-based optimisation techniques are applied to solve the resulting control optimisation problem in real time. To deal with the computational complexity of MPC in real traffic networks, a computationally efficient MPC method for optimising flows at urban intersections is proposed in van de Weg, Keyvan-Ekbatani, Hegyi, and Hoogendoorn (2020), based on a linear formulation of the link dynamics. In Li and De Schutter (2022), the signal settings of all intersections are regulated by applying distributed model-free adaptive predictive control, that is a data-driven approach relying on the massive amounts of traffic data generated every day.

Traffic signal control can be coordinated with CAV control in case of a mixed traffic scenario, i.e. a scenario in which human-driven vehicles and CAVs co-exist and share the same infrastructure. In Liu, Zhao, Hoogendoorn, and Wang (2021) this situation is addressed by proposing a two-level optimal control approach for integrating traffic signals and cooperative vehicle trajectories at intersections: the upper layer determines the optimal signals, and the lower layer optimises trajectories under each feasible signal plan. A similar problem is addressed in Liu, Zhao, Hoogendoorn, and Wang (2022) with a single-layer approach, in which the signal phase lengths and the accelerations of the CAVs are optimised to maximise comfort and to minimise travel delay, subject to motion constraints on speeds, accelerations and safe following gaps. The coordination policies for CAVs at intersections have become a relevant research topic recently (see the survey by Jackeline and Malikopoulos (2017) for more details). To address the intersection collision avoidance problem, Colombo and Del Vecchio (2015) show that avoiding a collision of CAVs is equivalent to a scheduling problem, the solution of which yields constructing a least restrictive controller to ensure that the state of the system is maintained within the maximal controlled invariant set. In Chalaki and Malikopoulos (2021) a decentralised optimal control framework for CAVs crossing adjacent signal-free intersections is proposed to minimise energy consumption and improve traffic throughput.

A complementary option to local traffic signal control is represented by perimeter control, allowing to regulate the traffic flows exchanged between neighbourhoods of the urban network by changing the green times of the traffic lights on the boundaries between these regions. In Sirmatel and Geroliminis (2021) nonlinear MPC schemes for perimeter control are developed and closed-loop stability of the system is proven, while in Mercader and Haddad (2021) perimeter control is addressed by proposing a resilient multi-variable control framework for traffic networks subject to possible cyber-attacks. In Kouvelas, Saeedmanesh, and Geroliminis (2017) a data-driven technique is integrated with model-based design, since the perimeter control regulators derived from linear approximations of the nonlinear dynamics are enhanced in real-time with online learning and adaptive optimisation.

Besides traffic control strategies acting at the system level, in recent years other control schemes have been designed for single vehicles mainly for emission and energy consumption reduction. Among them, it is worth mentioning eco-routing, corresponding to plan the routes for each specific vehicle, given its origin and destination, and eco-driving, consisting in the computation of vehicle trajectories along a given route, considering technical limitations of the vehicle and environment constraints as traffic lights. The interested reader is referred to Othman, De Nunzio, Di Domenico, and de Wit (2019) for more details on these aspects and, more in general, on traffic control strategies for improving environmental sustainability.

3.3. *Alternative solutions to private cars*

Even if traffic control methods are more and more reliable in managing the flows of vehicles in cities, they cannot be completely efficient in peak hours when the traffic demand is too high. The only solution to this issue is to work in the direction of encouraging non-motorised transport, when possible, or to incentivise the use of public transport and shared mobility solutions. Walking and cycling are surely important for a healthier lifestyle and for increasing accessibility, and they can be promoted thanks to dedicated pedestrian-bike paths and restricted access to the city centre for private vehicles. At the same time, the use of public transport can reduce not only energy consumption and pollutant emissions but also congestion. Vehicle sharing will also be key to sustainable mobility in the cities of the future by reducing the need for parking and helping in better exploiting the vehicle capacity. Thanks to all these alternative solutions, the users of a smart city can find in dedicated digital platforms their preferable option, even multi-modal, i.e. integrating different means of transport (e.g. public transport, car sharing, bike sharing, walking). However, the definition of methods for enforcing compliance to smart mobility policies and then, for inducing people to behave in a responsible manner is still an open problem. In Ferraro, King, and Shorten (2018), for example, some control-inspired methods are proposed to deal with the compliance issue.

The management of a smart public transport system represents an interesting challenge for the optimisation and control community. In Lam, Leung, and Chu (2016) a public transportation system based on automated vehicles is considered, addressing a scheduling problem to configure the most economical schedules and routes to satisfy the admissible requests, and an admission control problem to determine the set of admissible requests to produce maximum profit. Again, in Lam (2016) a public transportation system with automated vehicles is investigated, referring to a multi-tenancy case, and the pricing process for each service type is modelled as a combinatorial auction, in which the service providers, as bidders, compete for offering transportation services. A possibility to incentivise public transport is to prioritise buses at signalised intersections via temporary signal adjustments such as green light extensions. These policies can be enhanced in presence of CAVs by enabling cooperation and negotiation between vehicles and the traffic signal control system, as reported in Seredynski, Laskaris, and Viti (2020), in which it is shown that a cooperative solution can reduce stops at signals and decrease travel times. To maintain the service regularity, besides the preferential treatment at signalised intersections, another control strategy for buses is holding, i.e. waiting for additional time at stops, as discussed in Laskaris, Seredynski, and Viti (2020), in which a rule-based holding algorithm integrated with a cooperative driver assistance system is developed.

The main idea underlying sharing policies is to use transport systems on an ‘‘as-needed basis’’ instead of owning them, leading to the concept of Mobility-as-a-Service (MaaS). One potential benefit of ride sharing is the increase in system efficiency, which depends on the operational policies adopted and on the transportation scenarios (Ruch, Lu, Sieber, & Frazzoli, 2021) and which can have relevant impacts on traffic conditions (Beojone & Geroliminis, 2021). Fleets of self-driving vehicles providing on-demand mobility services jointly with public transit are studied in Salazar, Lanzetti, Rossi, Schiffer, and Pavone (2020), for which a pricing and tolling scheme is developed to reach the system optimum. Another crucial issue in vehicle sharing systems is re-balancing, i.e. sending vehicles from areas with an oversupply of vehicles to areas with high demand, leading to interesting optimisation and control problems to be faced. For instance, in Carron, Seccamonte, Ruch, Frazzoli, and Zeilinger (2021) this problem is treated for the case of self-driving vehicles, for which a discrete-time model with time delays is proposed and an MPC approach is discussed. A bike sharing system is studied in Swaszek and Cassandras (2020), where a time-dependent replenishment policy for each station is developed and a receding horizon controller, working in an event-driven way, is applied to find the optimal routes of replenishment trucks. Routing and re-balancing policies are also addressed in Wollenstein-Betech et al. (2021) for a mobility-on-demand system with CAVs, jointly acting with public transit under mixed traffic conditions, i.e. in presence of traditional private vehicles. In order to investigate the impact of smart mobility modes, an agent-based simulation framework is proposed in Bucchiarone, De Sanctis, and Bencomo (2021), where the cooperative integration of CAVs is achieved by a decentralised control approach.

3.4. *Road pricing and incentives for sustainable mobility*

Many smart mobility policies are based on pricing or incentivising strategies in order to orient the users' behaviour towards a system optimum configuration. It is indeed well known that selfish routing decisions in transportation networks are normally inefficient compared with socially optimal system-centric strategies, with the inefficiency due to selfish driving defined as Price of Anarchy (PoA) (see Zhang, Pourazarm, Cassandras, and Paschalidis (2018) for a data-driven approach to estimate the PoA). This difference between the social and the selfish behaviour of users may cause social compliance problems (Ferraro et al., 2018)

Different pricing strategies have been studied by researchers. For instance, in Annaswamy et al. (2018), trans-active control strategies are proposed, based on feedback through economic transactions, resulting in dynamic tariffs to be applied to increase the quality of urban mobility. In that paper, trans-active control is applied in two cases, to synthesise dynamic toll prices for traffic congestion reduction in highways and to dynamically route passengers in a city where not only conventional transportation services but also mobility-on-demand options are present. In Zheng and

Geroliminis (2020), pricing schemes are developed to improve both equity and traffic performance, in multimodal urban networks with users that are heterogeneous in terms of income level and value-of-time. In other approaches, pricing policies are combined with incentives to pursue efficient behaviours in urban mobility systems. For instance, Pfrommer, Warrington, Schildbach, and Morari (2014) consider shared mobility systems and propose a combined strategy for routing staff-based vehicles and for fixing real-time price incentives for customers, based on MPC principles. In Wang, Ma, Wang, and Qu (2021), the problem of relocation of vehicles in one-way car sharing systems is addressed by proposing an optimisation algorithm to define monetary incentives and surcharges at different stations and times of day.

3.5. *Parking management policies*

There is a very high impact of parking on mobility in a smart city. The accessibility of parking lots and the cost of parking strongly impact the users' travel behaviour. As a matter of fact, a high percentage of the travel time spent by the travellers in metropolitan areas is due to cruising for finding an available parking spot, with relevant impacts on traffic congestion, emissions, and fuel consumption. The most recent parking solutions are market-oriented and include pricing to incentivise socially desirable driver behaviours, as deeply discussed in the survey paper (Aljohani, Olariu, Alali, & Jain, 2021).

Among the control strategies devised to efficiently manage the parking process and to present intelligent solutions to drivers, we can mention the smart parking guidance algorithm proposed in Shin and Jun (2014), in order to suggest drivers, the most appropriate parking facility on the basis of the real-time state of parking lots, the driving distance to the facility, the walking distance from the facility to the destination, the parking cost, and the traffic congestion level. Moreover, a parking assignment strategy is proposed in Tran Thi Kim et al. (2020) to minimise parking expenses and to balance parking demand among multiple parking lots, both public and private, in case some are overloaded, and others are underutilised. In Zheng and Geroliminis (2016) dynamic parking pricing strategies are proposed to reduce congestion and to minimise the total travel cost of all users, by adopting a multimodal macroscopic traffic model capturing congestion dynamics at network-level in the presence of both cars and buses.

Other interesting problems from the control systems point of view are related to the definition of parking manoeuvres for semi-automated or self-driving vehicles. For instance, in Laurini, Consolini, and Locatelli (2021), parking manoeuvres are generated for self-driving vehicles by modelling each vehicle as a switched system in which each switching represents a change to a different type of motion. In that paper, this is considered a specific application of a more general theoretical framework, i.e. a finite-element approximation of the Bellman equation for the optimal control of switched systems.

3.6. *Air transport systems*

To meet increasing transportation demands in cities, the solutions adopted so far have been related to underground and ground-level transport. Despite the various attempts of city authorities and private companies to improve and optimise existing underground and grounded transportation systems, some systematic limitations of these transportation systems remain. Hence, researchers have been exploring alternative physical spaces for the development of future transport pathways, including the unexplored near-ground space, ranging from tens to hundreds of meters above ground level, leading to the concept of flying cars and flying car transportation systems (FCTSs). A detailed review on advances, methodological techniques, and challenges of FCTSs can be found in Pan and Alouini (2021).

In this context, we are witnessing a rapid growth in the development of Unmanned Aerial Vehicles (UAVs) for the urban environment. Path planning is one of the most relevant research themes to provide autonomy to UAVs in the execution of missions, by defining the set of waypoints to reach a destination, while satisfying some optimally criteria. This problem is addressed for instance in Primatesta, Guglieri, and Rizzo (2019) in which the path of UAVs is computed to minimise the risk to the population, by adopting a dynamic risk-map that associates discretised space locations with a suitable risk-related cost considering real-time conditions. Haddad, Mirkin, and Assor (2021) propose a modelling and control framework for low-altitude passenger and delivery aircraft systems, being inspired by road traffic control, resulting in an adaptive boundary feedback flow control which is robust to anomalies in technical devices and network communication links.

4. Smart energy systems

4.1. *Smart multi-energy supply and demand system*

There is an increasingly serious energy and environment crisis, which is one of the most important issues threatening the sustainable development of human society in the 21st century. Efficient and effective utilisation of renewable energy sources is becoming imperative. The European Union (as example) has formulated the target for at least 32% share of renewable energy and a 32.5% or higher improvement in energy efficiency.[1]

Today's energy grid structure is based on the assumption of a few large power plants since decades. Typical high base-power plants include nuclear power plants and coal-based power plants. These systems are capable to continuously serve high demands of electricity at low cost. In addition to this, it is assumed that the energy production can be controlled (within limits). With respect to the consumption, the production processes can be adjusted to the network load, and energy-consuming companies use the frequency-stable base load for uninterrupted (24/7) utilisation of their systems.

In contrast to this currently dominant production paradigm, future sustainable energy grids will have a very different structure. The number of energy producing systems will increase; each system producing smaller amounts. However, there are a few exceptions, like the floating Photovoltaic (PV) Power Station in Dezhou City, Shandong Province. It is currently the world's largest floating PV power station.[2] In addition to this structural change, an important aspect is that sustainable energy grids will not be freely controllable anymore. The production of sustainable energy is dependent on environmental conditions. Wind and sunlight, being the important sources of sustainable energy, cannot be increased, but the produced energy can only be reduced.

Overall, the evolution of smart energy networks will result in a very different structure and require control systems to cope with the changing dynamics in the grid (Veichtlbauer, Langthaler, Andrén, Kasberger, & Strasser, 2021). To increase the resilience and limit frequency fluctuations, more research and engineering is necessary towards dynamic stabilisation of energy networks. To reduce the risk of network failures, networks with a high share of renewable energy sources can be controlled using decentralised approaches. Stabilisation of energy networks so far has been mainly focusing on the producing side. To ensure resilience of future networks, it will be necessary, that many or all participants in the network, like producers, energy distributors, consumers, and intermediate storage, adapt to fluctuations in demand or production.

Only recently, demand side energy management has attracted more and more attention. Uncertain renewable energy supply and its impact on system operation can be reduced using smart control of flexible energy demand Guan, Xu, Jia, Liu, and Zhou (2018). The optimal control and coordination of multi-energy supply and demand systems is extremely important, and it is considered to be one of the most efficient ways to improve the performance of renewable supply–storage–demand system and achieve significant socio-economic benefits of energy saving and carbon reduction (Cui et al., 2019).

The multi-energy supply and demand system, which includes a smart energy system on both sides, is facilitated by information technology, requires research with respect to the IT infrastructure to achieve the optimal coordination of energy supply and demand. With this, it can optimally coordinate electricity, cooling, heating, renewable and other energy media, and provides advantages of the complementary characteristics of multi-energy flows and the elasticity of supply and demand. On the one hand, energy consumption in buildings accounts for about 40% of energy consumption, and has a huge flexibility (Xu, Hu, & Spanos, 2017). On the other hand, building is a typical multienergy system in the demand side, and the city energy system generally consists of various types of building energy systems, such as commercial buildings, office buildings, residential buildings, industrial plant buildings, etc. Therefore, many efforts have been made to optimise the multi-energy supply and demand system with the application of smart buildings. Existing research can be divided into three groups: system modelling, data-driven perception and prediction of demand profiles, and optimisation approaches.

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[1] https://ec.europa.eu/clima/eu-action/climate-strategies-targets/2030climate-energy-framework_en

[2] https://pandaily.com/huaneng-power-international-builds-floatingphotovoltaic-power-station-with-worlds-largest-single-capacity/

The first group focuses on the modelling of smart multi-energy supply and demand systems on the demand side. Generally, there are three ways to develop system models. The first approach are physics based models. These are developed using simulation software such as EnergyPlus (Nguyen, Reiter, & Rigo, 2014), TRNSYS (Lizana, Friedrich, Renaldi, & Chacartegui, 2018), etc. Here a precise model is formulated based on the laws of physics with differential equations, and it is applied to the dynamic performance analysis and evaluation of the multi-energy supply and demand system, but the development of this type of model is very time- and resource consuming and is difficult to be directly integrated when automating optimisation.

The second group of approaches are data-driven models. These types of models are developed using (data-driven) methods such as artificial neural networks (Ferreira, Ruano, Silva, & Conceicao, 2012), regression learning (Magnier & Haghighat, 2010), resistance–capacitance equivalence model (Fontenot & Dong, 2019), etc. In comparison with the first type, this results in black box models, computation efforts are lower, and the accuracy of the model may be difficult to be guaranteed and depends on the training data set. This type of model is also integrated with data-driven optimisation methods such as machine learning and reinforcement learning for optimisation purposes, which requires a lot of high-quality training data to improve the accuracy and feasibility.

In this group of approaches, some focus on the perception and prediction of demand profiles of the multi-energy supply and demand systems, since the flexibility of demand profiles is a basis for the optimal coordination of the multi-energy supply and demand systems. Perception and prediction methods of the demand profiles can also be divided into three categories, including white box (Li & Wen, 2014), black box (Amasyali & El-Gohary, 2018) and grey box-based methods (Zhao, Zhang, Zhang, Wang, & Li, 2020), depending on the principle of the perception and prediction methods used. The prediction of different types of energy demand, including cooling, heating, electricity, primary energy, steam, natural gas, are reviewed in Zhang et al. (2021). Since towns-peoples' behaviour and thermal requirements play a critical role in building operation, including its energy management, the perception and prediction of occupants' thermal comfort are very important for analysis of the flexibility in demand profiles. Prediction means include vote-predicted percent dissatisfied model (Fanger, 1970) and Pierce 2-node model (Gonzalez, Nishi, & Gagge, 1974), which are well-known thermal comfort model and are developed based on the thermal balance approach and is widely used to predict the thermal comfort from the perspective of human physiology. However, it is difficult to obtain all the parameters of the models by practical means which stops it from being used for dynamic thermal comfort prediction. To address these challenges, data-based models of thermal comfort were developed. An adaptive model of thermal comfort is developed in Brager and Dear (2001), which is formulated based on a relationship between the indoor acceptable temperature ranges and outdoor meteorological and climatological parameters. The methods
for the predictions of the thermal comfort are systematically reviewed in Martins, Soebarto, and Williamson (2022). Furthermore, in order to utilise both the physical knowledge and actual data feedback of the occupants, a hybrid physics-based/data-driven model for predicting the dynamic thermal comfort of occupants was developed to address the challenges caused by the diverse occupants' requirements with insufficient data (Zhou et al., 2021).

The third group are physic-principles-based, simplified models. This type of model is developed based on the physical principles with the simplification of the system state transition equations. The models are developed based on first-order or multi-order thermal state transition equations (Wang & Wang, 2013), linearisation of the non-linear dynamic process (Xu, Hu, Spanos, & Schiavon, 2017), Markov decision process (Martirano et al., 2017), etc. As compared with the first and second types of approaches, this type of model is always applied to the optimisation and control of the multi-energy supply and demand system, since it can address a trade-off between the accuracy and computational efforts. Furthermore, based on the specific definition of the operation constraints, the feasibility could also be guaranteed, but this type of model faces the curse of dimensionality, due to the coupling for multi-energy balance and conversion in the energy supply and demand system.

Optimisation methods of multi-energy supply and demand systems have been developed to improve the energy efficiency of smart energy systems focusing on the demand side. The optimisation methods can be divided into deterministic and stochastic methods, where the later methods include heuristics.

Deterministic methods mainly include mixed integer programming (Guan, Xu, & Jia, 2010), dynamic programming (Korkas, Terzopoulos, Tsaknakis, & Kosmatopoulos, 2022), MPC (Kwadzogah, Zhou, & Li, 2013), event-based optimisation (Wu, Jia, & Guan, 2016), which generally try to find the (global) optimal solution building on a strict theoretical basis. Limits to finding the optimal solution are computational resources and depend on the problem size. Due to the uncertain nature of the multi-energy supply and demand system, a series of stochastic optimisation methods have been developed to achieve stochastic matching of system supply and demand, among which multi-scenario-based methods (Mei et al., 2021), Latin hypercube sampling (Ju, Tan, Zhao, Gu, & Wang, 2019), capture the uncertainties by constructing reasonable scenarios. Optimisation-based methods are developed to ensure the robustness of the system operation (Liu et al., 2017), and other types of the methods such as chance constrained planning (van Ackooij, Finardi, & Ramalho, 2018) and heuristic algorithms (Mayer, Szilágyi, & Gróf, 2020) are also applied to the stochastic optimisation of the multi-energy supply and demand systems. Finally, in order to overcome the challenges of the collection of global information and the computational complexity caused by the problem scale, many distributed optimisation methods are developed. For example, a Lagrange relaxation-based distributed method is developed in Xu, Hu, and Spanos (2017) in a decomposition and coordination way. A multi-agent-based optimisation method is developed in Yang and Wang (2013) to capture the interaction between energy consumption and occupants. Other distributed methods have been reviewed in Wen, Liu, Rao, and Liao (2020).

Additionally, there are many approaches developed based on the combination of the three types of the models mentioned above. For example, a networked energy system model of the energy Internet was developed based on cyber–physical energy systems through the last two types of the modelling methods (Guan et al., 2018).

In general, although the above innovative modelling and optimisation of smart energy system approaches working on the demand side, there are still many challenges in this field that are open and need to be addressed. From the perspective of control and optimisation, the future interesting works on the optimal coordination of smart multienergy supply and demand systems may include: (1) the new model of the smart energy system has to be developed based on cyber– physical system to explicitly capture the multi-scale spatio-temporal coupling between the supply and demand and the interaction between the energy flow and information flow; (2) a hybrid physics-based/data-driven optimisation method has to be developed to utilise both the high accuracy of the physic part and low computational requirements of the data-driven part; (3) the intelligence of man–machine interaction has to be considered for operation of the multi-energy supply and demand system.

4.2. *Smart charging of electric vehicles*

Electric vehicles (EVs) have become important part of next generation ITS, and provided alternative to fuel-based automobiles, shifting energy demand away from fossil fuels. There is usually some flexibility in the charging of EVs. When an EV is connected to the charging station, the start time and finish time of the charging, and the charging power during the process may be controlled. Before the EV is connected to the charging station, even the charging location may be controlled (Long & Jia, 2021a) to take advantage of the intermittent renewable power generation and the dynamic time of usage (TOU) price of the electricity to achieve various objectives such as battery health protection (Muratori, 2018), peak procurement minimisation (Clement-Nyns, Haesen, & Driesen, 2009), and valley filling (Mozafar, Amini, & Moradi, 2018).

Due to the flexibility in charging, EVs are not only consumers of the grid, but also virtual power plants that may provide electricity back to the grid (known as vehicle-to-grid (V2G), and valuable ancillary services such as frequency control, spinning reserve, and peak load shaving (Zecchino, Prostejovsky, Ziras, & Marinelli, 2019). When combined with the distributed renewable power generators such as building-mounted solar panels, and on-site wind power generators, EVs may serve as a flexible load and a mobile battery, which may absorb excess on-site renewable energy and reduce frequency volatility.

Optimising the charging behaviour of EVs involves the information exchange and the energy transmission among multiple intelligent entities, such as buildings, charging stations, power grids, and EV aggregators (EVAs) (Jia, 2018). The charging schedule of the EVs may be determined centrally or de-centrally. Various centralised optimisation algorithms have been developed such as linear programming, nonlinear programming, stochastic programming and robust optimisation (Jia & Long, 2020). Due to the well-known curse of dimensionality, when the problem scale is large, it is time consuming for a central method to solve the problem. Heuristic and rule-based algorithms are common methods to reduce the computational burden (Jia & Wu, 2020). These methods are usually easy to implement, but they rely on some assumptions on the system and lack of performance guarantee. In light of this, event-based optimisation (Jiang, Jia, & Guan, 2022; Long & Jia, 2021b; Long, Tang, & Jia, 2017), ordinal optimisation (Long, Jia, Wang, & Yang, 2021) and hierarchical optimisation methods (Huang, Jia, & Guan, 2016) have been proposed recently to put forward new ideas for solving the problem quickly and efficiently.

Using these methods EVs and charging stations make individual decisions based on local information. If designed appropriately, this may achieve globally (near) optimal performance. Beyond efficiency and scalability (Yang et al., 2017), an additional advantage of the decentralised methods is the protection of privacy. Since EV owners only exchange some statistical information with EVAs (rather than personal information such as travel plans), their privacy is the better protected (Xing, Fu, Lin, & Mou, 2015).

In addition to the above discussion, the smart charging of EVs also has an important influence on other participants, such as marketing design and operation of the EV fleet, the position and sizing of charging stations and the ancillary services of the state grid. Detailed reviews can be found in Jia and Long (2020).

5. Smart data centres

Data centres are one of the key infrastructures of smart cities. In recent years, the global data centre market has expanded rapidly, with more and more data centres being built to serve the expanding Internet business. However, the energy consumption of data centres has also increased tremendously. It is estimated that the annual energy consumption of global data centres will reach 3000 TWh by 2030, accounting for 8% of the total annual global electricity consumption (Jones, 2018). After the optimisation of the data centre's preliminary site layout, the research about the energy-saving and reliable operation control is considerably critical. The energy-saving and reliable control of data centres is a critical component in helping us build a greener smart city, which has profound significance for the sustainability of smart cities.

Most energy consumption in typical data centres is due to the IT equipment and cooling system (Dayarathna, Wen, & Fan, 2015; Van Heddeghem et al., 2014). It is certainly important to design, develop and deploy energy-efficient IT equipment. However, in the rest of this section, we focus more on the operation optimisation of the cooling system, which is comparatively much easier to implement.

The increasing energy consumption of data centres requires better thermal management to improve energy efficiency and ensure the thermal security of the servers simultaneously. To solve the energysaving and reliable control problem of data centre cooling systems, most existing methods in industry are based on a two-stage framework. In the first stage, an approximate system model is established by mechanism analysis, which usually includes fluid dynamics, heat transfer and mechanical principles. In the second stage, the optimal control sequence is obtained by solving the energy-saving constrained optimisation problem. A common practice in data centre cooling system control is to change the air conditioning temperature set-point. The traditional control methods include local PID control on supply/return air temperature (Durand-Estebe, Le Bot, Mancos, & Arquis, 2013) (which is the mainstream method in the industry at present), expert knowledge, MPC (Lazic et al., 2018), etc. However, these methods may be restricted to use simplified models in the first stage and may not take full advantage of the operational data collected online in the second stage.

Model-free RL learns the optimal policy through dynamic interaction with the environment and without knowing the detailed model of the environment. This suits the practical interest especially when a detailed model is not available. In recent years, some reinforcement learning algorithms such as Deep Q Network (Van Le et al., 2019), Trust Region Policy Optimisation (Moriyama et al., 2018), Deep Deterministic Policy Gradient (Chi et al., 2020; Li, Wen, Tao, & Guan, 2019) have been already studied and applied to the energy-saving and reliable control of the data centre cooling system and achieved good energy-saving performance (Duan et al., 2020; Jia et al., 2020; Kumar, Khatri, & Diván, 2020; Linder, Van Gilder, Zhang, & Barrett, 2019; Liu, Wong, Ye, & Ma, 2020; Thein, Myo, Parvin, & Gawanmeh, 2020; Yang, Wang, He, Sun, & Zhang, 2019). Despite some considerable advantages of model-free reinforcement learning algorithms as aforementioned, the implementation in practice still faces many challenges. In order to prevent the over-heating of servers, model-free reinforcement learning algorithms cannot be trained directly in the real data centres. Researchers have to use the Computational Fluid Dynamics (CFD) simulation software to establish the simulation model, which is more or less different from the real environment. Most of the aforementioned experiments have performed only on the simulation platform. In addition, most reinforcement learning algorithms are sensitive to hyper-parameters. It remains open how to generalise a policy learned from certain simulation scenario to other scenarios that have not been simulated before. An even further question is how to transfer a learned policy from one data centre to another. Due to these concerns, there are quite some hesitations when companies try to adopt RL algorithms in their data centres. Hence, follow-up work should consider how to improve the accuracy of the CFD model, and how to select a good policy even when the model is not accurate. In the meanwhile, a learned policy with explainable structures would be easier for application.

6. Conclusions

The past decade has witnessed the tremendous development both in theories and in technologies in control for smart systems. We have reviewed their applications to various aspects related to smart cities in this work. With more autonomous systems deployed in our modern society, there have been growing interest to improve not only the smartness of the systems in cities, but also their intelligence to exhibit situation awareness as well as self-X capabilities. These would certainly improve the production efficiency, transportation efficiency, energy efficiency, comfort satisfactory, and help to achieve carbon neutrality in the near future.

Due to the limit of space and the expertise of the authors, in this work we have focused on several selected subsystems in smart cities including enterprise and manufacturing systems, transportation and mobility systems, energy systems, and data centres. On the one hand, many optimisation problems in these systems share the same framework and may be described as programming or Markov decision processes. When the problem scale is large, decentralised, or distributed optimisation algorithms have attracted great interest both in research and in practice. On the other hand, there are domain-specific structures and constraints in each such systems. For example, temporal logic constraints easily show up in manufacturing systems. And there is an increasing number of low-volume-high-mix manufacturing demands, requiring fast modelling and model verification, real-time and low-cost controller design and execution, and high resilience to dynamic system change. Capacity constraints are pervasive in transportation systems. Supply–demand matching are key constraints in energy systems. The correlation between the job scheduling and the air conditioning system control is crucial for energy efficient data centres.

Note that there are several other important subsystems of smart cities that are not included in this study, such as the public health management, the city infrastructure monitoring and maintenance, and the protection of water resources. We hope this study may shed some light to the control of these systems, too.

Given all the development of control for smart systems in cities, we would like to conclude our discussion with the following list of challenges for each subsystem of smart cities to be reached by 2030 (see Table 1).

Smart Enterprise and Manufacturing Systems Manufacturing is one of the main drivers for CO2 and other climate-relevant impacts. The increase in efficiency and effectiveness is strongly demanded by society for reaching carbon neutrality. This also improves value creation through cost-effective solutions by means of products and services provided to the market. To this end, cyber–physical systems approach (including cyber–physical production systems) will be key enablers to support decentralised intelligence with more capabilities on heterogeneous computing nodes, framed within interoperable information systems and coordinated/collaborative relationships across different parts of smart manufacturing enterprises. This provides a basis for higher adaptability and resilience, ranging from the single factory to the production network level. A key effort will be the adoption of circular economy to enable sustainable processes. Circular strategies will be further developed and exploited by manufacturing companies, such as cleaner production and resource efficiency strategies to reduce energy and material consumption, regenerative strategies – including reuse, re-manufacturing, recycling, and waste management – to exploit the residual value of products, or servitisation to contribute to the optimal use and maintenance of products. Overall, data-driven control and optimisation methods will be essential to achieve cost-effectiveness, while reducing environmental impacts by the manufacturing sector.

Smart Transportation and Mobility Systems Mobility also has a large impact on the environment and, more broadly, on the achievement of sustainability goals. The increase in efficiency and automation of vehicles and the development of monitoring and control tools for

Table 1

Grand-challenges for smart cities to be reached by 2030.

Subsystems	Challenges
Smart enterprise and manufacturing systems	• Increase in efficiency and effectiveness by smart decision making based on interoperable information systems • Further exploitation of circular strategies for manufacturing by adaptive smart systems
Smart transportation and mobility systems	• Increased efficiency and automation of vehicles • Smart control of traffic flows • New mobility paradigms
Smart energy systems	• Smart control of networks of renewable energy sources and consumers
Smart data centres	• Supply–demand matching with renewable energies • Inventing new data centres that use natural cooling and ventilation • Policies learned from reinforcement learning algorithms and with explainable structures
Systems-of-systems	• Network of Smart Systems • Integration and interoperability of smart systems to improve the overall impact on sustainable development goals

improving traffic flows are surely important fields of research in this direction. Anyway, the most challenging and promising directions for smart mobility research seem related to new mobility paradigms that help to reduce and better balance the transport demand. This includes the development of sharing mobility resources, innovative public transport systems and optimisation-based digital platforms supporting personalised multi-modal transport solutions. All these innovations will become part of the daily life of citizens around the world, because of research and development of suitable optimisation and control approaches.

Smart Energy Systems All new developments for the smart city will need energy. Therefore, the intelligent management of renewable energy is an important factor for fighting climate change. As a matter of fact, the energy system is reshaping itself to provide more interaction and more flexibility to the rest systems in smart cities. In particular, decision making across multiple spatial and temporal scales is in demand, which will utilise data, computing, and human experience to achieve real-time near-optimal system-level performance.

Smart Data Centres Data centres will be responsible for 8% of the annual energy consumption globally by 2030. Among the many subsystems in smart cities, data centres are particularly rich in data. It would be challenging but in demand to achieve carbon neutrality in this subsystem, not just by purchasing in carbon market, but more by supply–demand matching with renewable energies and by inventing new data centres that use natural cooling and ventilation. Control theory will play a crucial role in this effort. Policies learned from reinforcement learning algorithms and with explainable structures could help companies in the implementation.

Systems-of-Systems The individual descriptions above already show that there are many and strong links between the sub-systems. For example, manufacturing depends on data centres for implementing data-driven intelligence. Manufacturing also involves supply chains and the associated transport logistics. The machines require stable energy networks. By making individual smart city systems interoperable and allowing free information flows between different points of views, the smart city will meet new opportunities for smart control on a very different level (see Table 1).

Declaration of competing interest

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

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