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Survey of advances and challenges in intelligent autonomy for distributed cyber-physical systems

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Abstract: With the evolution of the Internet of things and smart cities, a new trend of the Internet of simulation has emerged to utilise the technologies of cloud, edge, fog computing, and high-performance computing for design and analysis of complex cyber-physical systems using simulation. These technologies although being applied to the domains of big data and deep learning are not adequate to cope with the scale and complexity of emerging connected, smart, and autonomous systems. This study explores the existing state-of-the-art in automating, augmenting, and integrating systems across the domains of smart cities, autonomous vehicles, energy efficiency, smart manufacturing in Industry 4.0, and healthcare. This is expanded to look at existing computational infrastructure and how it can be used to support these applications. A detailed review is presented of advances in approaches providing and supporting intelligence as a service. Finally, some of the remaining challenges due to the explosion of data streams; issues of safety and security; and others related to big data, a model of reality, augmentation of systems, and computation are examined.

1 Introduction

The trends of grid [1], cloud [2], and high-performance computing (HPC) [3] are a culmination of what could be termed the third industrial revolution of digitisation and automation of individual systems and processes [4, 5]. The current wave of Internet of things (IoT) [6], edge [7], fog [8] computing, as well as big data [9] with deep learning [10] and Internet of simulation (IoS) [11] are the trends of the fourth industrial revolution (Industry 4.0) [12, 13]. With applications within Industry 4.0, the Internet of everything and anything [14], and beyond where every part of society and industry is digitally integrated, there are significant challenges that must be addressed. This paper therefore presents a detailed review of existing state-of-the-art and core challenges that must be addressed to achieve the desired level of intelligence, automation, and integration in emerging systems.

Across each of the domains, there have been significant technological advances in enabling cyber-physical system of systems (SoS) to be integrated together in a holistic fashion. However, there remain substantial challenges that must be addressed. The first of these is the explosion of big data streams [15, 16] resulting from large-scale data collection in the integration of systems from smart cities, autonomous vehicles, IoT, smart manufacturing, healthcare, as well as the aerospace, defence, through to finance industries.

Secondly, the increasing intelligence and interconnectivity of these systems into a shared environment requires a shared *model of reality* [17]. This *model of reality* provides a set of shared perspectives on reality that can be integrated with simulation and decision support systems via simulation in the IoS [11]. These perspectives can provide to the cyber-physical systems that exist within each of the domains intelligence as a service. Necessarily unifying the standards to integrate both the existing and future technologies [18] will require significant research and development.

Additionally, the service economy [19] will continue to act as the cornerstone for these developments. Specifically from a service-oriented architecture (SOA) perspective [20, 21], the services and micro-services may be hardware systems or devices, human individuals, Cloud hosted software [software as a service (SaaS)], or even simulations (SIMaaS). The aggregation or composition of these services into workflows and subsequently, the workflows into services will provide a scalable approach to design and augmenting existing systems [22, 23].

Further, the trends of cloud, edge, and fog computing must be pushed to their limits and combined into hybrid models with extensive virtualisation to abstract away from individual cloud or HPC providers. Developing the physical and virtual computational and communication infrastructure will underpin each of these areas. This includes technologies such as 5G and long-term evolution (LTE) [24], which along with software-defined networks will have to be advanced to improve reliability, bandwidth, and security.

The remainder of this paper is structured as follows: in Section 2, the motivation for cyber-physical SoSs integration and automation is presented across a range of application domains. In Section 3, the underlying computing infrastructure is explored from cloud computing through to the edge and fog paradigms [25]. Section 4 discusses some of the core challenges that have yet to be addressed as a result of the expansion of autonomous IoT systems. In Section 4.2, the need for a shared *model of reality* is discussed to augment systems with additional contextual awareness. Also, finally, some of the security challenges are outlined in Section 4.3 before conclusion are presented in Section 5.

2 Emerging applications

The emergence of the Internet of anything and everything [14] from IoT [26] is driving smarter and more context-aware systems and applications. These concepts augment the technologies related to cloud and edge computing [27] and allow computational power to be balanced against location which has an impact on both network latencies and security. The ubiquitous management of the computational systems and communication networks is anticipated to be augmenting and penetrating most cyber-physical systems that we interact with on a daily basis within the coming decade.

One example domain is that of cooperative robotics where advances in autonomous systems [28] are enhanced with additional computational capability from the cloud. The resulting emerging field of cloud robotics combines the two research fields to provide intelligence services to robots from the cloud [29–31], assist in robot interaction [32, 33], and allows robots to provide services back to the system [34, 35].

There is now a growing trend to adopt these, and related, research concepts into society and across industry as automated intelligent systems. This paper explores in detail the state-of-the-art and challenges particularly related to manufacturing and infrastructure for smart cities. The rest of this section explores more widely the applications and domains where there is a current focus on autonomy and connectivity which includes defence and security, aerospace, and finance. The adoption of IoT and IoS within each of the domains is also explored before the rest of this paper explores the detail around infrastructure and intelligence and ongoing research.

2.1 Smart cities

Smart cities are one of the latest trends in urban planning but as yet do not have a unified definition in the literature [36]. The lack of a standard definition results from the variety of cities that are being coined as *smart* as well as how and why they are being transformed [37]. The range of definitions include a focus on computing, connectivity, data, efficiency, infrastructure, and services [38–40]. Alternatively, they focus on the social, cultural, and governance aspects [41, 42]. Across these broad definitions, there are numerous 'smart' cities internationally.

However, as the global population continues to grow, and continues to migrate closer to cities with in excess 50% of the global population currently residing in cities, it is essential to understand how a city becomes 'smart' and what the end or intermediary results look like [43]. As discussed in both [43, 44], one of the fundamental aspects of a smart city is understanding its multidimensionality. As shown in Fig. 1, there are the technological factors, the business or institutional aspects, the city and human factors, and then the virtual dimension of data [44]. This can be alternatively defined as existing systems/agents (which includes humans) that must be refactored; the computational infrastructure including cloud, IoT, and IoS technologies; and the data dimension.

We consider a smart city to be cyber-physical SoS heavily reliant on intelligent autonomy, distributed computing, IoT, and IoS such that it brings together technology, governance, and society to manage and monitor power and communication infrastructure, the environment, traffic, and other aspects of the city for the benefit and well-being of its inhabitants through ubiquitous sensing and embedded intelligence, and facilitates economic growth through innovation, connectivity, and data aggregation [17, 45]. For example, applying robotics within a smart city may include applications for repair and maintenance [46, 47] or driverless transportation [48] which is discussed in more detail in the next section.

2.2 Autonomous vehicles

Transportation infrastructure provides many opportunities for intelligence and autonomy. Driverless cars and trucks being one of the most publicly visible systems being developed; though as yet, there is still high level of concern surrounding their adoption [49]. To map their development, different levels of automation are defined by how involved a human driver is in controlling the vehicle [50]. Some of the foundational technologies providing lower levels of autonomy already are included in advanced driver-assistance systems, while the higher levels of automation are still being developed [51].

For fully autonomous driving, several real-time systems must interact to perform perception, planning, and control [52]. There are a number of potential strategies, early approaches mapped actions directly from sensory input, but modern approaches use a mediated approach where the immediate environment is reconstructed and recognised before actions are determined [53]. Hybrid approaches with minimal reconstruction have also been developed [54].

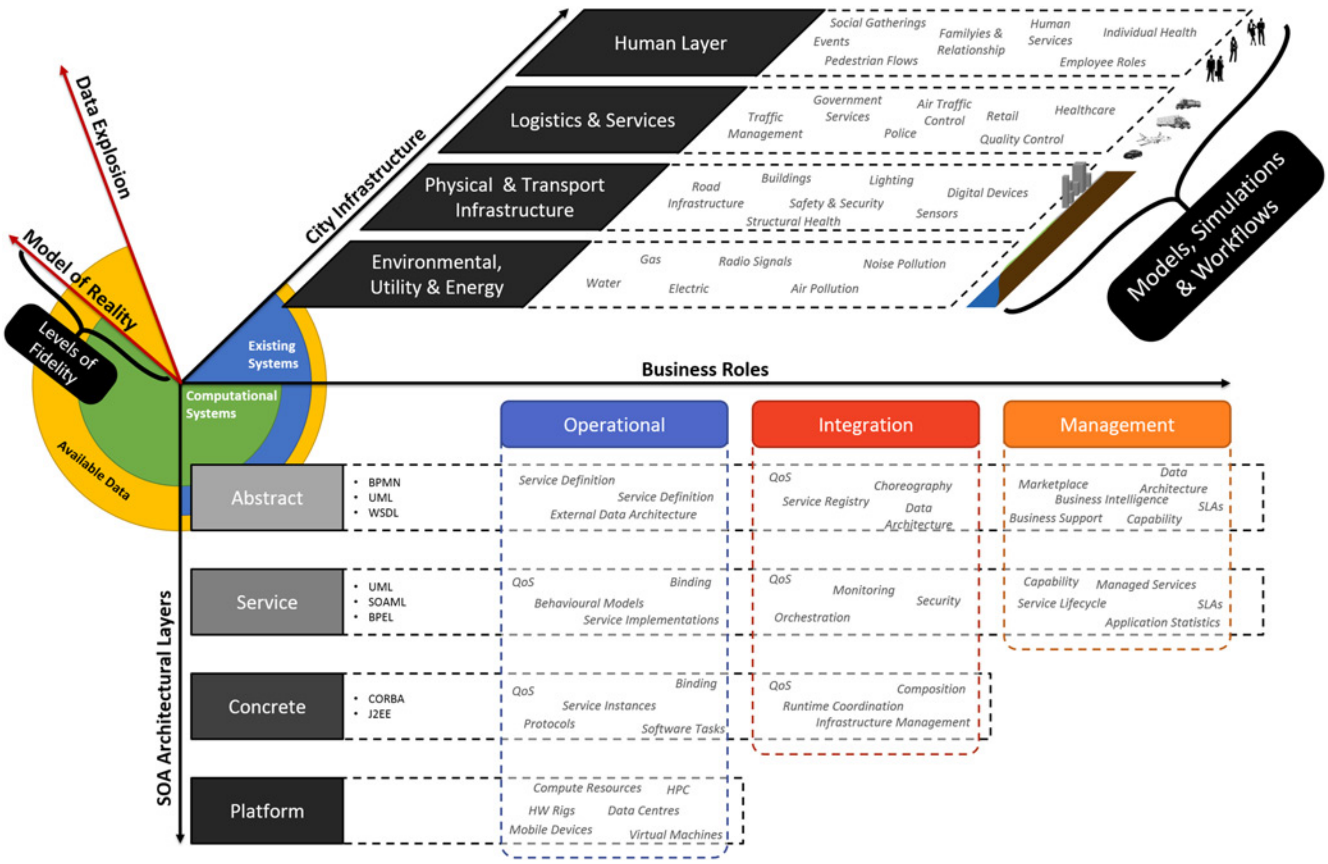

Fig. 1 *Layers of abstraction in SOAs (business and technical), and physical cities [44]*

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The success of the autonomous driver relies heavily on correct perception and localisation; therefore, there have been numerous data sets provided, the most commonly used being the KITTI benchmark [55] which focuses on motion estimation. Others have noticed a need for localisation across a range scenarios and conditions [56].

Autonomous drivers are often assumed to operate in isolation, but there is growing interest in the possibility for interconnected vehicles, an *Internet of vehicles* or a *vehicular cloud* [57]. The interconnection of these systems has the potential to allow for holistic traffic management and the use as a service of the data generated by the vehicle.

This trend is not only limited to land vehicles; however, ships [58] and aerial vehicles [59] are also being automated for similar transportation tasks.

2.3 Power and energy efficiency

The growing need for renewable energy generation is driving a move from the existing power grid infrastructure to more distributed generation units known as microgrids [60, 61]. Adding intelligence to this increasingly distributed power grid to match generation with demand has been called the smart grid [62]. The vision of smart grids is one where intelligent, demand-side systems manage smart, renewable energy generation combined with energy storage to provide smart production, management, and distribution [63]. These applications rely on large-scale data collection and processing [64], meaning that the communication and computing infrastructure is a vital component in the smart grid [65] with communication security being of particular importance [66]. Given that the intelligence of many of these power systems depends on large-scale computer systems, the efficiency of data centres is a crucial component in increasing overall energy efficiency. At present, 3% of global power is used in data centres [67], up from 1.3% in 2010 and 0.8% in 2005 [68]. Data centre power consumption is not only the result of computational power consumption, the efficiency metric of data centres power usage effectiveness (PUE) is a ratio of power consumed by IT and non-IT equipment [69]. Cooling equipment power consumption can be as much as 50% of total power consumption [66]. As demand increases, improving the efficiency of data centres requires intelligent scheduling [70], modelling of workload patterns [71], and improvements in cooling [72]. There are also further efficiency gains achievable by utilising the waste heat generated by the data centre [73]. There has been increased effort to model the power consumption of data centres [74] for prediction of PUE and optimise the data centre [75].

2.4 Smart manufacturing and Industry 4.0

The technology of the digital revolution, sometimes regarded as the third industrial revolution [4, 5], is now reaching a level of maturity and pervasiveness the fourth industrial revolution dubbed *Industry 4.0* is emerging [76]. The technologies of personal computing have grown to incorporate devices from laptops through to smart phones, smart watches, and numerous sensors being used throughout products and in daily life. At an industrial level, there is almost ubiquitous use of HPC and cloud computing platforms that provide massive degrees of computational power which can be combined with the emerge of connected technologies such as 4G, 5G, and LTE [24].

These advances facilitate the integration of intelligent automation into the manufacturing value chain as Industry 4.0 [76, 77]. The adoption of IoT devices within the manufacturing process and within customer products, known as the industrial IoT [78], provides a data-driven system. These *smart factories* are able to utilise the data and readings from the IoT devices to flexibly adapt to changing demands in the marketplace. Within factories themselves, the real-time data streams generated by the interconnection of large numbers of autonomous systems allow the factory to gain a level of self-awareness, calculating machine health, behaviour, and self-optimising operations [13].

Within this the fourth industrial revolution, the trend will move from merely connecting real-time big data streams from IoT devices within factories and products to an closed-loop ecosystem bringing together IoT with the devices from the factories and the products; data streams from those devices and systems; IoS with modelling and simulation to analyse and use those data streams to improve products and improve manufacturing processes [44].

2.5 Health and well-being

The application of autonomous systems to the domain of healthcare is growing. The adoption of evidence-based medicine [79] and the widespread record keeping of the medical community provides opportunities to apply big data analytics to the field [80]. There is also large amounts of additional health data being generated by the marketplace of wearable health devices within IoT [81]. Security of this online, personalised health data has become an increasing concern [82] and the move towards blockchain record systems [83] aims to facilitate the secure sharing of patient records. Additionally, there has been a move to utilise robotic systems in patient care to reduce the demand on healthcare services [84].

One such example is the work by Howard [85] which involves physically embedding a microprocessor on human brain tissue to monitor, decode, and then manipulate brain signals. This work has application in researching diseases such as Alzheimer's and Parkinson's. By connecting the devices, as IoT systems, to the network signals could potentially be monitored in real time and the huge amounts of collected data can be analysed. This could result in identifying disease progression without the need for observing the likes of motor and speech symptoms [86].

3 Computational infrastructure

Underpinning the applications discussed in the previous section is the distributed computational infrastructure which includes cloud [87, 88], edge, and fog computing. The later refers mostly to the low power, geographically distributed devices forming the IoT [6, 26]. This section explores each of these before hybrid infrastructure approaches are explored in the following section.

3.1 Cloud computing

Cloud computing is focused on the provision of an on-demand network accessible and easily configurable computing resources [88]. It is typically defined in terms of the service layers [89], shown in Fig. 2. The uppermost layers within a cloud computing architecture are the service layers comprising SaaS [23], platform as a service (PaaS), and infrastructure as a service (IaaS). The software layer may comprise both applications, functions, and data as services (FaaS, DaaS). The resource abstraction layer provides the containers and virtual machines typically used to host the service layers within the cloud. Below the various levels of abstraction lies the underlying operating systems [90].

Beyond the service layers, there are various deployment models [91]. The most common are public and private clouds, the latter being dedicated to a single user or organisation. A growing trend is that of hybrid clouds which use mixtures of the private and public models, often to facilitate scale-up. A further trend is that of joint or virtual clouds which creates another level of abstraction presenting a unified perspective on cloud services from a range of providers [92].

3.2 Edge computing

The cloud computing era provided a mechanism for computation and data processing to be performed off-site at a low cost. However, the centralised nature of the cloud introduces significant limitations due to communication bandwidths and latencies that have been shown to

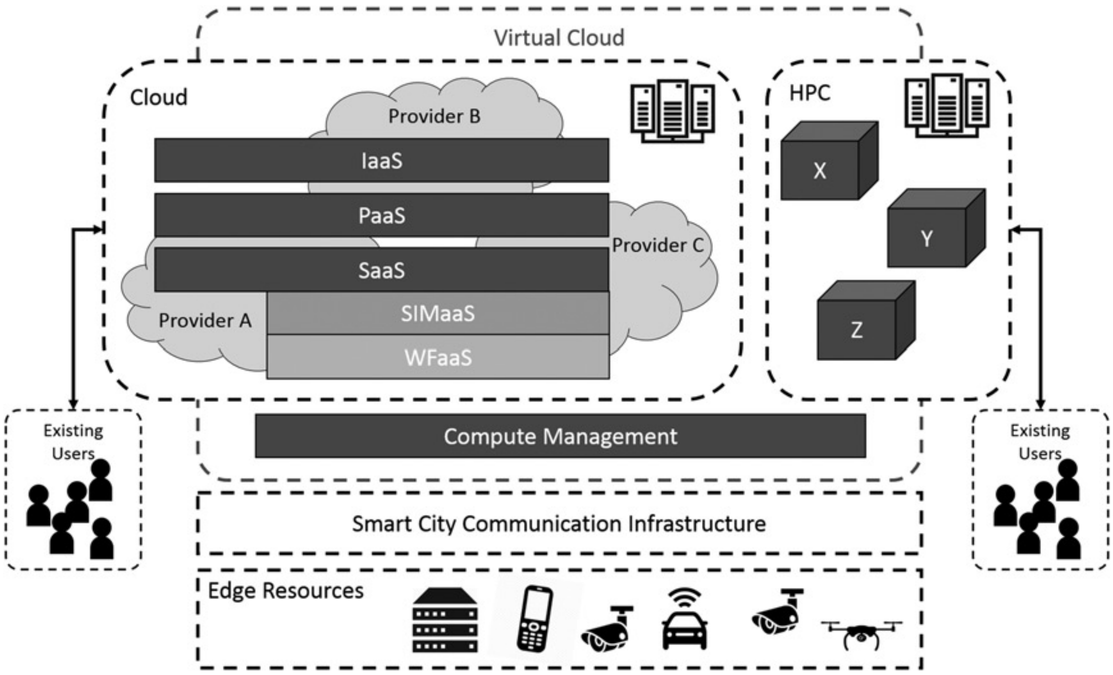

Fig. 2 *Cloud layers of abstraction for IoT and IoS [17]*

be inappropriate for latency-sensitive applications such as health monitoring or autonomous vehicles [93]. Therefore, with the availability of smaller and cheaper but yet powerful compute devices, the edge computing paradigm brings the processing back closer to the devices themselves [7].

Edge computing is sometimes regarded as synonymous with mobile cloud and cloudlets. The former focuses entirely on the use of mobile devices which are typically low powered and location-aware [94]. Mobile devices are therefore limited in the level of data processing and computation that they can provide leading to the conceptualisation of cloudlets [95]. Cloudlets are small clusters of compute resources, typically of a high density, that are accessible to nearby devices [96].

3.3 Fog computing

We have discussed how the cloud computing paradigm does not suit certain domains and applications; however, the edge paradigm also has limitations due to the level of processing required by some of those same applications. These require the ability to connect with and share with other system's data in the way that a cloud would facilitate while requiring the mobility of edge computing [97].

Therefore, we now have the emerging hybrid paradigm of fog computing [8, 98]. In order for this paradigm to successfully achieve integration of these systems, the reliability of every aspect must be managed and guaranteed with a level of quality of service [99]. The fog paradigm provides a virtual layer between data centres and IoT devices that extends the virtual cloud paradigm discussed previously. In doing so, it must also encapsulate specialist compute facilities such as HPC as shown in Fig. 2. Appropriate deployment of fog computing as hybrid unifying model across distributed computing paradigms may provide a suitable approach to mitigate the issues of scalability, fault-tolerance, elasticity [7], as well as facilitating management services to detect failures [98].

3.4 Services

Services and SOAs are now a common paradigm for designing distributed systems and addressing the growing complexity of systems. Services can be used to easily augment existing systems without affecting system performance by providing new or updated services and promoting reuse of existing services. In adding intelligence to systems, especially those interfacing with infrastructure, it is important that the new functionality or the upgrade not interfere with operation of the original underlying systems.

A marketplace of services can facilitate discovery and integration of services which can be integrated together into workflows to perform specific functions [21]. Fig. 1 shows an example of services in a potential smart city adapted from [44]. The figure demonstrates the multi-dimensional nature of cyber-physical systems:

- City infrastructure layers including utilities, transport, through to human residents.
- Business service layers reflecting operation and management aspects.
- Technical computing architectural layers, shown here in terms of layers of an SOA.
- Layers of data and *models of reality* that provide the intelligence and information to allow such an integrated cyber-physical system to operate.

Further, these systems can be derived into three overlapping groups:

(i) Existing systems which may be partially integrated together.
(ii) Computational systems including those needed for further integration, automation, and data processing.
(iii) Data which brings them all together along with context.

In example shown the services, systems, devices, and individuals integrate across the city and different infrastructure levels by providing services that are readily combined with those from pother providers.

Integrating pre-existing systems remains challenging due to lack of compatible standards, and becomes ever harder with the need to augment those existing systems with intelligence, autonomy, and data collection. In Fig. 1, the existing city and compute infrastructure is integrated, this includes both business and the conceptual layers [21] – and additionally the Cloud computing: SaaS, PaaS, and IaaS providing a fifth utility. One remaining challenge with SOA is the automatic re-factoring of services to ensure continuous operation and future compatibility [100, 101].

4 Remaining challenges

So far, this paper has explored the wide range of emerging applications related to autonomous cyber-physical systems and taken a detailed look at the technologies that currently underpin these advances. There are however several challenges that have yet to be resolved, many of which will continue to grow, that this section explores.

4.1 Challenge: data explosion

Throughout the discussion, so far the term *data explosion* has been used in conjunction with the IoT and big data trends. Big data analytics provide techniques for the analysis and visualisation of extremely large data sets [102]. Specifically, these data sets are too big to store on a single machine and so must be distributed. Already, the growth of data is exponential [103] and increasing data collection and further cloud services will only accelerate this further [104]. Very quickly, this could lead to a situation where we are no longer able to process the explosion in data collection.

This challenge of data explosion refers to the fact that what we currently define as big data is a snapshot of the scale of data that will be communicated and processed in the near future. Firstly, the type of data is diverse ranging from scientific data collected by NASA through to social media interactions or the Internet itself. Companies such as Google, Facebook, Microsoft, Alibaba, Baidu, and Amazon are already processing terabytes of data on a daily basis and storing several exabytes. This progression and the generation of several exabytes of new data every day means that it is anticipated that will be in excess of 40 zettabytes by 2020 which is beyond the scale that any existing research on big data has ever attempted to process or analyse [9, 105–107].

This data explosion is being driven partly by the growth in IoT, reaching between 20 and 30 billion devices by 2020 [108–110], and the large-scale collection of data primarily for product improvement and customer analysis. It is envisioned that this absolute collection of data will enable machine learning techniques to provide models and simulations as part of IoS that can support the desired level of autonomy [15]. IoT promises ubiquitous sensing and a network of data-driven devices, a network of things [111], that is unprecedented today, which will then be augmented with intelligence and analysis from IoS [11].

This rapid increase in the number of devices and quantity of data results in a series of challenges that must be imminently addressed. Firstly, the quantity of data is too large to be continuously stored and must therefore be filtered. This filtering will have to occur at stages across a physical network which would be overwhelmed by the quantity of communication. Instead, there will have to be further advances in stream processing to collect relevant information from sources and discard the rest [16, 112].

Secondly, the variety of data sources and heterogeneity of data types and formatting results in a huge multidimensional space from which it is infeasible to manually identify meaningful features for conventional machine learning approaches. Therefore, it is necessary to develop techniques for the automatic identification of features and intelligent and meaningful dimensional reduction in order to retain the most relevant information.

Thirdly and most controversially is the challenge of understanding and managing data privacy. With this level of data collection, which is necessary to achieve the desired level of automation, there are associated privacy costs. For example, in the context of autonomous vehicles, there remains a question of what data needs to be collected in order to facilitate full autonomy. With autonomous vehicles, there also remains a question of liability which requires additional data to be recorded to provide context for adverse events. It is therefore posited that a solution must be found that balances the freedom and privacy of individuals with the data required by regulatory frameworks, the data required by manufacturers, and data required by other interacting autonomous systems [113, 114].

4.2 Challenge: shared model of reality

Simulation and virtual engineering are already heavily utilised in most engineering disciplines for the development of cyber-physical systems. The increasing complexity and greater application of cyber-physical systems has seen a growing need for integration between simulations from different domains in order to fully understand system level interactions and behaviours. This in turn has led to the development of tools and standards to enable simulation integration and co-simulation: DIS [115], HLA [116, 117], FMI [118], and FDMU [119]. The growing trend towards online, easily integrated simulations has been called the IoS [11].

Similar to the way IoT connects devices, IoS allows the connection of simulations. This result in the benefit of being able to construct large co-simulations from component simulations of parts and mitigates the difficulty of developing large-scale monolithic simulations [18, 120]. Additionally, this allows individual system to be developed in a more agile way, responding faster to changes in requirements new environments [22]. The ability to readily compose detailed simulations is of particular importance for intelligent systems, especially if they augment existing systems as the additions can be extensively tested as virtual prototypes before deployment. Simulations can also be utilised to provide training environments for artificial intelligence (AI) [54, 121] and can also provide decision support and predictive power (see Fig. 2). With large-scale distributed simulations, this parallel simulation of reality can be shared across many agents leading to a consensus of the environment and potentially a knowledge beyond that perceivable by a single agent's sensors.

There are trade-offs when developing simulations between level of detail, speed of execution, and accuracy. For example, a heat exchanger can be modelled as a series of one-dimensional (1D) equations or a 3D computational fluid dynamics simulation. To ensure a timely response in real-time systems, the detail and scope of a simulation may be reduced, whereas increased detail may be more important in systems using simulation for longer term planning. In both cases, using simulation to assist and enable intelligence may require large amounts of computing power. In mobile or battery-powered systems, where power usage and weight are a key design criteria, it may be necessary to offload computation and utilise cloud or HPC computing for simulation.

There are a number of challenges to the implementation of IoS and its wide use in intelligent autonomous systems. The problem of automated simulation integration is a particular challenge [22, 122]. Integrating an arbitrary collection of simulations remains infeasible for a number of reasons including: differing levels of fidelity, incompatible data types or representations, incompatible timesteps, or solvers. Often, widespread integration of simulations is impossible as many simulations do not scale to the required level [123]. Another issues are that simulations are often created from specific viewpoints and the requirements for the desired simulation may not match with any existing simulation. Even though there is increased interest in large-scale simulation and there are numerous benefits in its application to autonomous systems, there are still many open challenges and none of the existing standards satisfy all requirements for a true IoS [124, 125].

4.3 Challenge: safety and security

Earlier in this section, the issue of data privacy was discussed and challenges to maintaining safety and security are directly relevant. From the perspective of security, there remains an issue of providing practical solutions to system security without massively degrading performance and a comprehensive review of security within IoT is provided by Jing *et al.* [126].

One particular challenge with IoT and the continued increase in the use of data centres will be to find methods to inhibit denial-of-service attack (DDOS) attacks from IoT devices. An example of this is the Mirai attack that gained control of devices and loaded malware into memory [127]. Alternatively, there was the demonstration of remote code execution on IP CCTV and

DVR devices from which a DDOS attack could be launched [128]. Given the billions of IoT devices that are already connected, most of which are relatively unsecured, there is a clear need for a concerted effort to update existing systems to be more secure and develop new more resilient security techniques.

One concept that is gaining traction with cloud computing, and may be applicable to IoT, is that of performing computation on encrypted data, using homomorphic encryption, this can provide a significant performance improvement by removing the need to encrypt and decrypt data in the cloud [129]. Fully homomorphic approaches remain slow and therefore 'somewhat' homomorphic encryption techniques have been developed to improve performance, but at the cost of limiting the data values and types that can be processed [130]. Currently, these techniques only operate on numerical data and as such are limited to application of searching, sorting, and other arithmetic operations where the encryption process is order-preserving [131]. Therefore, for such techniques to become universally applicable, they must be improved to operate on more complex data types. Further, since the principle requires systems to operate on encrypted data, the intelligent systems, such as simulations (SIMaaS), must also be adapted to be able to do so. This in itself is a major challenge since there is normally internal state and internal parametrisation which may or may not be encrypted. It is also anticipated that future techniques involving IoT devices will utilise a mixture of native hardware and software encryption but in order to do so, there must be a clear set of security standards shared across systems and devices.

A further concept that is attracting attention is that of quantum-key distribution techniques [132] since they provide a mechanism to immediately identify if an unauthorised individual is listening on the communication. These techniques are currently limited firstly by the distance over which they can be used, currently limited to ~21 km [133]. By improving the detectors, the range can be increased to nearly 100 km and can be extended further by using repeaters. As the range and accuracy of detectors increases, these approaches are likely to form a part in defining security standards and protocols. In the same way, the recent adoption of blockchain technology [134] is likely to form a major influencer of future standards in the domains of finance and healthcare in particular [83]. However, it is questionable whether these approaches will be practicable for general data security. Therefore, as data processing becomes increasingly distributed, and operates in virtual clouds, there remains a challenge to certify the security and certain conditions that will be maintained.

Moving on from data and communication security, there remains the issue of guaranteeing the safety of these systems, in adherence with standards appropriate for each domain. Current safety critical systems are not typically connected via networks to other systems. However, as their complexity increases and their need for increased compute power grows, they will inevitably begin to rely on platforms such as cloud computing which are not typically used or designed for safety critical systems. Additionally, these systems are no longer statically defined but evolve using machine learning. There must therefore be mechanisms to consistently, automatically, and repeatedly evaluate the safety of any given system [135]. As a result, there have been recent calls for the development of *black boxes* to monitor adaptive systems that have AI [136, 137]. Alternatively, techniques such as provenance can be adopted which use historical data analysis to evaluate the performance of systems and alert regulators or engineers when the performance or behaviour deviates from expectations [138].

5 Conclusion

The technologies enabling greater connectivity between devices and more distributed computing such as cloud computing, big data, and IoT are allowing for greater levels of intelligence and autonomy in cyber-physical systems. These include advances in Industry 4.0, smart cities, autonomous vehicles, and healthcare. These new paradigms and applications have the potential to radically change the way society interacts with cyber-physical systems.

However, this increased level of connectivity presents a number of challenges that must be addressed if the vision of large-scale autonomy and intelligence is to be achieved. An increase in connectivity and growing recognition of data as the world's most valuable resource will lead to a demand that may outstrip the ability to process, store, or even transmit data in the quantities being proposed. Automated integration and processing of data for data reduction will be a vital technology to allow for the large-scale data gathering being proposed.

Autonomous systems that control cyber-physical systems will process collected data either locally in edge and fog computing systems or in the cloud. Simulation is already being used to train and test intelligent systems in isolation. In the future, edge and cloud computing could operate in parallel to provide real-time simulations to distribute cyber-physical systems. By being able to readily integrate multiple simulations together, a high-fidelity training environment can be provided along with accurate prediction and ultimately, a shared model of reality in the IoS.

Additionally, there are still significant challenges in managing the security of collected data and distributed systems. Techniques such as homomorphic encryption and quantum-key distribution could help with security challenges but ultimately, this is a persistent challenge that must be continually addressed as exploits are found. Owing to this, systems need to be designed with agility in mind in order to be able to quickly react to changes in the security landscape. There should also be mechanisms for initial verification of safety protocol compliance along with mechanisms for continual evaluation of compliance to counteract any service performance degradation over time.

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