Chapter 1
Cyber-Physical Systems: An Overview

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1.1 Introduction

Cyber-physical system (CPS) is a complex and heterogeneous system with seamlessly integrated cyber components (e.g., sensors, computers, control centers, and actuators) and physical processes involving mechanical components, human activities, and surrounding environment [1]. CPS is capable of closely interacting with the surrounding physical environment through perception, communication, computation, and control. There are various CPS application domains including electric vehicle (EV), smart grid, health and medicine, smart home, and advanced industries, which promise substantial economic and social benefits.

The terminology of CPS was coined in 2006, when scientists and engineers from different discipline backgrounds started to work on the different aspects of CPS. System designers leverage scientific methodologies as well as powerful engineering techniques and tools for time or frequency domain analysis, pattern recognition, modern filtering, prediction, estimation, optimization, and machine learning to optimize CPS for high performance. Meanwhile, computer scientists and engineers have made breakthroughs in novel programming languages, powerful

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modeling formulations and advanced verification tools, energy-efficient computing techniques, compiler tools, embedded systems and software, and innovative methodologies to improve CPS reliability, efficiency, and security. However, the design and development of CPS face new challenges incurred by the ever increasing system scale and complexity, the interaction with the complex physical world, the adoption of distributed embedded systems, and the stringent requirements on reliability, efficiency, and security. A key method addressing these challenges is to co-design physical and cyber components. For example, CPS design needs to model, simulate, and verify the sensing, calibration, computation, control and communication infrastructures, the software and hardware platform, and the surrounding physical environment, simultaneously.

Although CPS has been studied for more than 10 years, its development is still in an early stage. There are plenty of opportunities and technical challenges in ensuring system reliability, efficiency, and security of multiple domains such as smart grid, smart building, electric vehicle, and healthcare. Below, we first elaborate the opportunities, challenges, and recent work in these CPS application domains, then introduce the solutions to improving system QoS from reliability and security perspectives, and finally present the design methodologies from design automation, data analysis to hardware support.

1.2 Applications

In this section, we give a systematic review of typical CPS applications including smart grid, smart building, electric vehicle, and healthcare.

Smart Grid As shown in Fig. 1.1, smart grid is a system that integrates modern communication technologies, emerging energy storage devices, and renewable energy sources with the traditional electricity grid to facilitate electric energy generation, distribution, and transmission with high efficiency, reliability, and security [2]. In a smart grid, cyber systems and physical systems are closely coupled to address various challenges such as the intermittency of regeneration and the uncertainties in the energy market. A particularly interesting aspect in smart grid CPS is the dynamic electricity pricing mechanism. In reality, utility companies always adopt dynamic pricing mechanisms to balance the electricity load. For example, a common pricing strategy is that the electricity price of peak hours is set to higher than that of valley hours. This strategy would encourage customers to use household appliances during valley hours and hence mitigate the electrical overload at peak hours. On the other hand, with the help of the massively deployed smart metering infrastructures, smart homes can use the dynamic pricing mechanisms to control household appliances such that electricity energy is saved and electricity bill is reduced [3]. Consequently, there will be a large amount of reduction of energy consumption in the entire electricity grid. According to statistics [4], if each resident house saves 5% energy, the reduction in energy consumption across the USA will

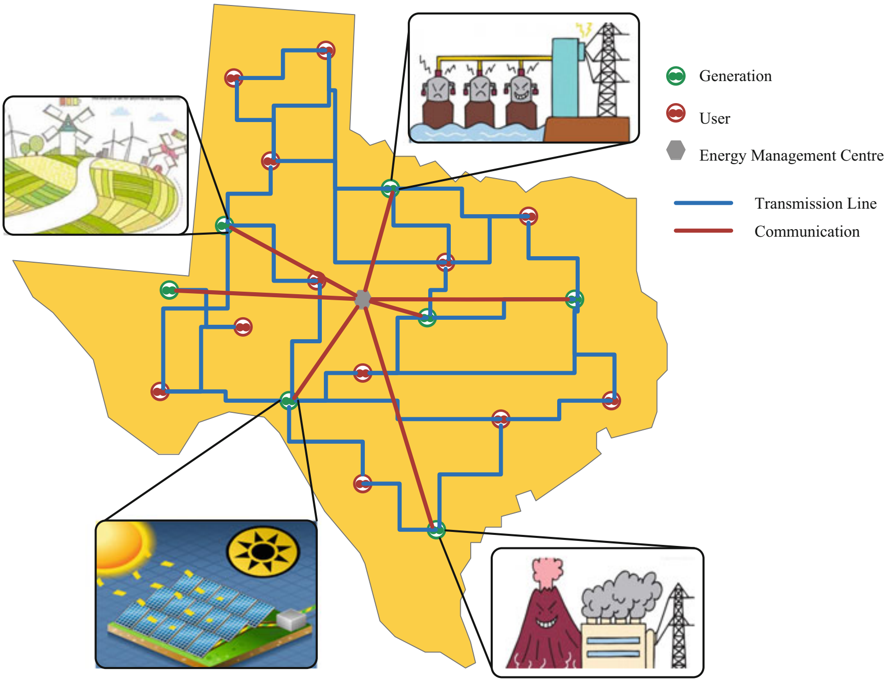

Fig. 1.1 Illustration of smart grid

be approximate to the amount of energy savings achieved by removing 52 million cars. As it is effective in decreasing electricity bill, dynamic pricing mechanism is also widely adopted by cloud service providers to minimize the cost [5, 6].

Smart Building Smart buildings (as shown in Fig. 1.2) play an important role in human daily life since they provide a more comfortable life environment with reduced energy consumption (and hence electricity bill) as compared to traditional buildings [7]. To meet the increasing demand for high comfort level and intelligent building services, heating, ventilation, and air conditioning (HVAC) systems need to be controlled efficiently in smart buildings to reduce energy consumption and provide a good thermal performance [8]. On one hand, simulation is one of the most important steps at the design stage of smart buildings. In this step, energy consumption and thermal performance are predicted to assist energy and thermal-aware optimization. In the simulation, heating and cooling systems, equipment, and building components are fed into the building simulation platform to reduce energy consumption and mitigate temperature using heat balance algorithms [9–11]. On the other hand, implementation of advanced sensor calibration for extending the lifetime of smart buildings is an indispensable step in the design of smart buildings. Different from traditional sensor calibration, the sensing matrix of advanced sensors deployed in smart buildings depends on weather as well as the position of sensors and

Fig. 1.2 Features of smart buildings

parameters of the building (e.g., material characteristics, geometry, and equipment power per area) [9, 10]. However, in practice, it is hard to obtain all of these complex information. This brings new challenges in the design of smart buildings.

Electric Vehicle Electric vehicle (EV), as a green and clean transportation tool, has many advantages in terms of energy conversion efficiency and environmental protection over traditional vehicles. As a CPS, EV also consists of actual physical systems and cyber components for computation, control, and sensing. The two parts work together to make EV energy-efficient and environmental friendly. Due to these advantages, EVs have been widely studied in the literature and deployed in the real-world. However, the increasing penetration level of EV brings new challenges and problems. These potential issues include voltage deviation as well as power quality and overload problems caused by uncoordinated charging of EVs. In particular, massive amounts of stochastic charging to EV have negative effects on the capacity and stability of EV systems and power systems. To overcome these challenges, numerous coordinated charging strategies are proposed in the recent years.

Health and Medicine CPS is widely adopted in medical and healthcare applications to provide health related services. Health and medicine are always considered as one of the most important issues in the world. Many countries are suffering severe shortage of healthcare, which causes an increasing health cost. Currently, a major concern is the ineffectiveness to process the massive data in CPS health and medicine applications. As a result, advanced computing frameworks and infrastructures are necessary.

An innovative revolution in computing and communication networks has been achieved in recent years. As the feature size of semiconductors enters nanometer era, biochips become smaller and smaller [12]. In addition, with the development of near-threshold and low-power integrated circuit design, biochips have higher performance and lower energy consumption [13]. These advanced integrated circuits and semiconductor technologies integrated with CPS bring many benefits to health related applications. For example, advanced biochips facilitate in vivo implantation of human to monitor health condition by interacting with the monitoring center. However, medical CPS faces extensive challenges, such as security and reliability [14]. Different from common computing applications, in order to obtain multi-model information from biological, cognitive, and social networks, various resources with interior sensing abilities are adopted to extend beyond computer-connected physical process [15]. Therefore, some standards are modified to comprise interdependent information networks, smart devices, and mobile devices.

Another typical application of medical and healthcare CPS is biochip manufacturing. Biochips can control the movement of droplets of picoliter volumes. Digital microfluidic biochips are used in biomolecular recognition to perform point-of-care clinical diagnostics. These point-of-care tests can be used in resource-limited areas [16]. With biochips, the reactions of flash chemistry can yield desired substances with high selectivity [17]. The biochips can promote the miniaturization and the automation for the bioassays of samples [18].

1.3 Quality of Service

The purpose of designing and deploying CPS is to provide a high quality of service (QoS) for specific users. In this section, we focus on measuring the QoS of CPS from two representative aspects of reliability and security.

Reliability Typically, the CPS reliability refers to the ability of correctly performing system intended function under a given set of environmental and operational conditions during a given time interval [19]. Recently, Cao et al. [20–22] investigate reliability enhancement algorithms for both mixed-criticality uniprocessor embedded systems and heterogeneous multiprocessor systems. Zhou et al. [23] explore reliability and temperature constrained task scheduling for minimizing system makespan on heterogeneous multiprocessor platforms. Meanwhile, the authors further design a framework to deal with the energy, makespan, and lifetime issues in reliability-driven task scheduling [24]. Haque et al. [25] address the problem of satisfying a specific reliability goal for periodic real-time tasks executing on a multiprocessor system with minimum energy consumption. Li et al. [26, 27] propose a set of feedback control-based algorithms for reliability improvement of EtherCAT-based networked systems.

Security The interdependence and interaction between cyber components and the physical world inevitably bring new security risks to CPS. A cyber disturbance, either an occasional component failure or a malicious attack, may cause catastrophic consequences in CPS. For example, the attacks of destroying transmission lines by increasing energy load during peak hours or undermining generators by increasing frequency disturbance are very likely to result in widespread electricity blackouts [28]. Therefore, it is necessary to investigate useful methodologies to guarantee security for CPS. In the area of CPS security, abnormal detection is an important step to identify either short-term or long-term abnormal system behaviors. For short-term abnormal detection, the popular techniques of support vector machine and Gaussian mixed model are shown effective to detect physical attacks, cyberattacks, and data attacks for energy theft in the smart grid [29]. In order to enable long-term abnormal detection, a partially observable Markov decision process is proposed to find the optimal action that maximizes the expected reward or, equivalently, minimizes the long-term impact of cyberattacks in CPS [30].

1.4 Methodologies

In this section, we give a brief introduction to three representative design methodologies in CPS, including design automation, data analytics, and hardware support.

1.4.1 Design Automation

In the design of CPS, multiple factors need to be considered, such as energy consumption, reliability, timing, fault tolerance, and security. Design automation tools can be used to develop high performance CPS through complex analytical modeling, efficient simulation, synthesis, and verification. There have been several instructive attempts (e.g., [9]) to bring CAD methodologies developed for traditional integrated circuit design to deal with the new CPS research challenges, such as how to improve CPS performance subject to performance constraints and how to reduce power consumption in energy harvesting systems. CAD methodologies have also been adopted to optimize different metrics such as schedulability, timing (efficiency), reliability, energy, and security for CPS. For instance, Wei et al. [31] propose a novel model predictive control-based algorithm for decreasing the peak energy demand and total energy consumption. Furthermore, the authors develop a system-level approach to co-schedule the usage of grid electricity and battery storage with building heating, ventilating, and HVAC systems [32]. Cao et al. [33, 34] put forward energy-efficient algorithms to schedule approximate computation tasks. As far as economic interest is concerned, the customers' home appliances are scheduled at the community level to minimize the energy purchasing expense from utilities at the market level [35].

For improving system security, Lin et al. [36] propose a general security-aware design method to enhance security with certain design constraints in a whole framework. This method can be further applied to handle a security-aware design problem for vehicle-to-vehicle communications with dedicated short-range communication technology. In order to handle pricing cyberattacks, Liu et al. [37] develop a partially observable Markov decision process-based detection algorithm with a policy transfer graph and reward expectation for the potential future impact. In addition, the authors also devise a detection technique based on partially observable Markov decision process and Bollinger bands to analyze the energy theft cyberattack [30]. Zheng et al. [38] combine control-theoretic methods at the functional layer and cybersecurity techniques at the embedded platform layer, and address security together with other design metrics such as control performance under resource and real-time constraints.

Similar to integrated circuit design, the whole process of CPS is very complex such that manual design cannot achieve the optimal solution in homogeneous domains. Given this, Sztipanovits et al. [39] build a comprehensive design tool suite for CPS. Nuzzo et al. [40] conduct a top-down mapping of application-level constraints with a bottom-up propagation of platform constraints to find the right composition of platform components that meets an application's requirements. Maasoumy et al. [41] propose a co-design approach to analyze the tight interaction between the embedded platform and the control algorithm. Deng et al. [42] propose an integrated synthesis flow to address the supply chain problem in CPS.

1.4.2 Data Analytics

Recently, machine learning technologies are developed to handle frontier challenges arising from the presence of uncertainty, multiple time-scales, multiple energy resources, the security issues, and the reliability issues related to modernized CPS. It is expected that these machine learning can improve CPS performance in terms of above aspects. To be specific, Chen et al. [43, 44] develop a linear regression model to determine the temperature variation of each location and the most important factors contributing to it. Lin et al. [45] adopt an adaptive model to reduce the huge computational cost. A classification is proposed by Sridhar et al. [46] to identify cyberattack by highlighting dependencies within the cyber-physical control parts required to facilitate the smart grid computations and communication. A supervised learning algorithm is developed by Jones et al. [47] to infer formulae to distinguish between desirable and undesirable behavior. Zhang et al. [29] utilize a generic model to identify electric theft under imbalance data. Esmalifalak et al. [48] adopt both supervised and unsupervised machine learning techniques for stealthy attack detection.

1.4.3 Hardware Support

In CPS, many diverse cyber devices are required to meet the increasing QoS requirements. As mentioned in the previous section, CPS includes three kinds of devices, i.e., sensors, communications systems, and processors. With the rapid development of semiconductor fields, sensors become more and more sensitive, precise, adaptive, and intelligent. For example, wearable equipment like smart watch have many emerging functions such as monitoring sphygmus, blood pressure, and sleep time. The data collected by these functions can be easily sent to a computing center for medical purposes, with the help of real-time efficient communication systems.

The limited computational resource also brings challenges in CPS. Specifically, with the development of machine learning and deep learning, the collected data can be accurately analyzed. However, the hardware platform is very expensive and energy-consuming. In recent years, some researchers (e.g., Zhang et al. [49]) seek to deploy deep learning algorithms onto computational resources limited hardware platforms, which provides many opportunities in broadening the application domains of CPS for high performance computing and data analysis.

1.5 Conclusion

In this chapter, we give a high level review of CPS development and research directions from the aspects of applications, QoS, and methodologies. We first summarize recent works on classical CPS applications of smart grid, smart building, electric vehicle, as well as health and medicine. We then discuss the works on improving reliability and security of CPS. We finally discuss CPS design methodologies from the perspectives of design automation, data analysis, and hardware support.

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