Chapter 2 Machine Learning in Cyber– Physical Systems in Industry 4.0

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ABSTRACT

Cyber-physical systems (CPS) have emerged with development of most great applications in the modern world due to their ability to integrate computation, networking, and physical process. CPS and ML applications are widely used in Industry 4.0, military, robotics, and physical security. Development of ML techniques in CPS is strongly linked according to the definition of CPS that states CPS is the mechanism of monitoring and controlling processes using computer-based algorithms. Optimizations adopted with ML in CPS include domain adaptation and fine tuning of current systems, boosting, introducing more safety and robustness by detection and reduction of vulnerabilities, and reducing computation time in time-critical systems. Generally, ML helps CPS to learn and adapt using intelligent models that are generated from training of large-scale data after processing and analysis.

INTRODUCTION

The term Industry 4.0 refers to the fourth industrial revolution that been developed by Germany from 2011. The basic principle of Industry 4.0 is the adoption of the internet or the interconnectivity between all industry components from product manufacturing to user experience. This technology integration involves the Cyber-Physical System CPS field in the development of Industry 4.0. Internet of Things (IoT) is an important element in Industry 4.0 which enables the connectivity between various manu-

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facturing components in the industrial environment and outside at consumer's experience environment. The development of Industry 4.0 is not only concerned by connectivity solutions but also should offer a self-optimized manufacturing feature that enables using data acquired from consumers while experiencing the products. This self-optimization feature should address the potential problems and issues in both manufacturing and consumer environments. Users satisfaction is considered as one of the whole process, which is dependent on the predictive solutions given by analyzing system data by using Machine Learning algorithms (Jia et al., 2016). For the importance of ML use with CPS in industry 4.0 applications, this chapter provides detail about the concepts of using ML integration to CPS for optimizing industry 4.0 monitoring processes and control.

This chapter is organized as follows. The chapter background is presented and followed by the concept of ML in CPS applications. The chapter provides detail about ML in CPS for industry 4.0, discussing the model architecture and other considerations related to self-aware machines, embedded low latency applications, and fog computing. Also, it provides a brief idea about the classifications of ML for attack detection in CPS 918-920(Košťál and Holubek, 2012). Moreover, the chapter reviews the cyber-physical production system concept, in addition to adaptive and cooperative production systems. The most common use cases of AI in industry 4.0 applications are presented in this chapter, gives a brief review of the possible future research directions related to ML/CPS in industry 4.0.

BACKGROUND

Cyber-physical Systems and industry 4.0 are bonded concepts in the industrial revolution. CPS is the infrastructure of industry 4.0 standard, which describes the new industrial environment proposed in industry 4.0. It involved intelligent senses and controls to approximately all manufacturing processes. This development doesn't consider an ordered pattern of innovations, but a package of functionalities and features are introduced in a parallel way (Jiang, 2017). Where while the development of some technology another one is been developed too. Researchers and developers had found the way along to achieve objectives of industry 4.0 by adopting the ML techniques with the industrial process which adds the intelligence feature. The approach of intelligent manufacturing is been developed from the 70th and 80th of the last century, while the official initiation of ML in industrial manufacturing can be tracked lately to the 90th. Instead of industrial manufacturing, ML has various types of techniques for different types of applications. The most common ML methods include statistical methods, rule induction, genetic algorithm, nearest neighbor clustering, decision trees, and neural networks (Lee, 2018).

The impact of ML was obvious in the development of industry 4.0, as can be also obtained by the revolution of CPS architecture that is standardized by ANSI with the introduction of IEC/ISO 62264, ISA-95 Architecture, then 3C, 5C, and 8C architectures are developed. While this rabid development, revolutionary systems are raised such as intelligent manufacturing systems (IMS), holonic- and agent-based systems. From these developments, the usage of ML in different processes is obtained, as resulted in various developing technologies such as self-aware machines, real-time and low latency embedded applications, fog computing, cooperative manufacturing systems, and context-adaptive autonomous systems. Is also obtained the major role of ML is security and privacy application in industry as in intrusion detection and threats mitigation. A highlighted use cases for ML that led into an industrial artificial intelligence are predictive maintenance, quality assurance, and prediction, optimization of manufactur-

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