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A fog computing industrial cyber-physical system for embedded low-latency machine learning Industry 4.0 applications

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ABSTRACT

Industrial cyber-physical systems are the primary enabling technology for Industry 4.0, which refers to an emerging data-driven paradigm focused on the creation of manufacturing intelligence using real-time pervasive networks and operational data streams. These cyber-physical systems enable objects and processes residing in the physical world (e.g. manufacturing facility), to be tightly coupled and evaluated by advanced predictive analytics (e.g. machine learning models) and simulation models in the cyber world, with the intention of realising self-configuring operations. Thus, this research presents an industrial cyber-physical system based on the emerging fog computing paradigm, which can embed production-ready PMML-encoded machine learning models in factory operations, and adhere to Industry 4.0 design concerns pertaining to decentralisation, security, privacy and reliability.

1. Introduction

Industrial cyber-physical systems enable objects and processes from the physical world, to be tightly coupled with compute, communication and control systems in the cyber world [1]. Cyber-physical interfaces connecting both worlds facilitate transmissions using wireless sensors, smart phones, and tablets, to name a few [2]. Conceptually, these cyber-physical interfaces manifest 'cyber twins', where real-world physical objects are represented as virtual objects in the cyber-world. In turn, these virtual objects may be individually and/or collectively analysed, interrogated or simulated to derive operational insights and inform decision-making.

A prominent emerging network paradigm promising to bridge physical and cyber-worlds is that of the internet-of-things, which comprises internet-enabled devices and gateways to sense, collect, send and receive data [3]. In terms of manufacturing, this may involve interactions with sensors, controllers, actuators, radio-frequency-identification (RFID) tags, global positioning systems (GPS), and high-definition cameras [3], to name a few. Naturally, these continuous and pervasive interactions produce large data repositories (i.e. big data) that describe factory operations [1]. Once enough high-quality data has been captured, these large datasets can be analysed using machine learning to make useful predictions (e.g. equipment failures).

At present, cloud and service-oriented computing appear to be the most prominent compute paradigms used to implement industrial cyber-physical systems [4–15]. However, traditional cloud computing naturally conflicts with Industry 4.0 principles relating to decentralised decision-making and reliable real-time control. Although cloud and service-oriented computing can support distributed engineering scenarios, intelligence and processing (e.g. decision-making) typically remain central (e.g. cloud server), which means distributed clients depend on consistent and resilient connections with the cloud. However, given industrial cyber-physical systems may comprise networks-of-networks with uncertain bandwidth, compute paradigms dependent on persistent connections to centralised services are not suited to real-time automation and control scenarios. To better address these Industry 4.0 concerns, compute paradigms supporting decentralised and autonomous decision-making may be considered. Both multi-agent systems [16,17] and fog computing [18–21] exemplify such paradigms, where compute nodes operate autonomously to deliver intelligence on the outer edge of pervasive networks, without being concerned with persistent connectivity. In addition to removing dependencies on external connectivity, the local and autonomous operation of these paradigms can also reduce network traffic (i.e. less requests), improve scalability (i.e. deploy more nodes as needed) and enhance data security (i.e. data does not leave the facility). Hence, this research presents an industrial cyber-physical system that employs fog computing to deploy and embed production-ready machine learning models, and compares

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the reliability and consistency of the implemented fog cyber-physical interface with that of a traditional cloud interface.

2. Industrial cyber-physical system

2.1. Proposed fog topology

Fig. 1 illustrates the composition of the fog computing topology for delivering real-time embedded machine learning using cyber-physical interactions. The cloud platform stores production-ready machine learning models encoded as Predictive Modelling Markup Language (PMML) for different engineering applications (e.g. equipment prognostics), which are disseminated and executed by fog nodes deployed within the facility's local network. Although these local operations promote data security and privacy, factory-to-cloud communications depend on the facility's existing security policies and services governing internet communications. Once communications from the factory are received by the cloud, the request is authenticated using the fog node's 128-bit Global Unique Identifier (GUID). A cloud database of registered devices is used to lookup the GUID, identify the engineering applications handled by the node, and return relevant PMML models to download or synchronise. The downloaded PMML models are stored on the fog so they may be executed within the physical boundaries of the factory, and deliver real-time predictions and decision-making (e.g. control changes) without persistent connections to the cloud.

2.2. Technical architecture

Fig. 2 illustrates the technical components used to implement the industrial cyber-physical system. First, the *sensing layer* contains the industrial equipment and systems to continuously acquire real-time measurements, and an embedded software agent to mediate communications between physical and cyber environments. Second, the *fog layer* contains technical components to receive inbound data streams, execute PMML-encoded machine learning models, and return results. Finally, the *cloud layer* contains technical components to maintain metadata about each fog gateway deployed in the factory (e.g. engineering applications etc.), persist PMML-encoded models in a global repository, and discharge relevant PMML models to fog gateways as machine learning models are added or updated.

2.3. Performance assessment

A series of load/stress tests were applied to the implemented fog and cloud cyber-physical interfaces to evaluate their (a) *reliability:* maximum execution time, and (b) *consistency:* number of failed communications. These performance parameters were chosen given their fundamental importance to time-dependent control and engineering applications. The cloud and fog cyber-physical technologies used during the experiments employed standard out-of-the-box configurations to protect from potential biases, while experiments were executed in close proximity to reduce fluctuating environmental conditions (e.g. broadband throughput, local network activity etc.) contaminating performance measurements. These measurements were captured using a test computer hosting the open source load testing application JMeter. The JMeter agent was configured with experiment parameters to send, receive and measure transmissions for each cyber-physical interface. The OpenScoring engine was installed behind both interfaces to handle JMeter requests, and execute the PMML-encoded model using the data provided. The PMML model was derived from an existing Support Vector Machine (SVM) model that predicts faulty heating operations within industrial air handling units.

JMeter was configured with several scenarios that continuously increased the load on the cyber-physical interfaces. These stress tests instructed JMeter to simulate 50, 100, 250 and 500 concurrent connections (e.g. controllers, smart sensors etc.), and execute 1000 requests for each connection (e.g. 50 concurrent connections would result in 50,000 requests).

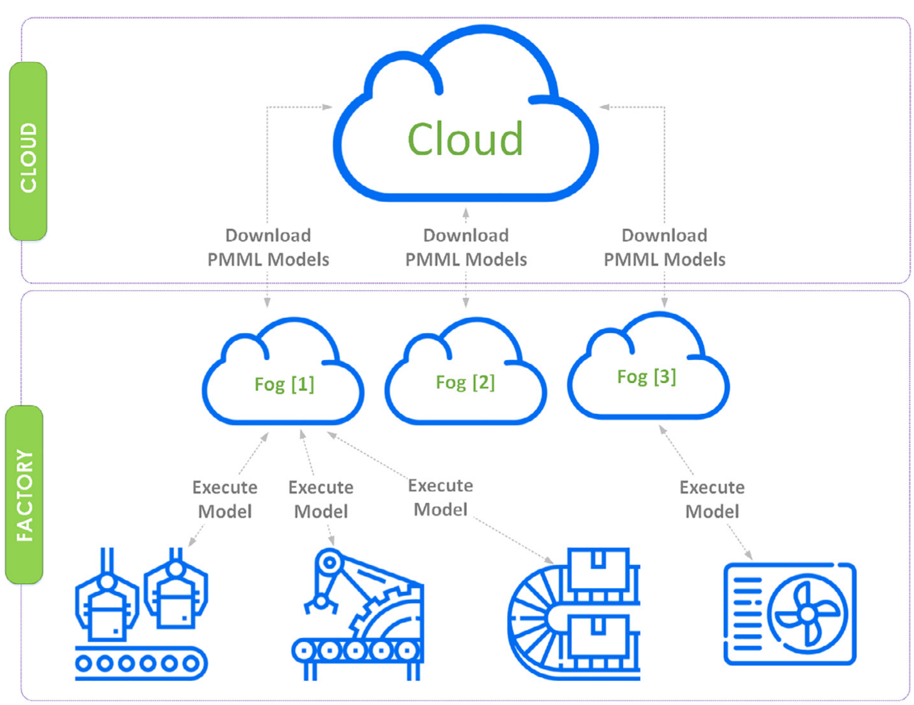

Fig. 1. Composition of fog computing with cyber-physical interactions.

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