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IoT-based production logistics and supply chain system-Part 2: IoT-based cyber-physical system: A framework & evaluation

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Internet of things-based production logistics and supply chain system-Part 2: IoT-based cyber-physical system: A framework and evaluation

Abstract

Purpose – The objective of this paper is threefold: (1) to present IoT-based CPS architecture framework to facilitate the integration of IoT and CPS; (2) to implement an IoT-based CPS prototype based on the architecture framework for a PL application scenario of in a case study; and (3) to devise evaluation methods and conduct experimental evaluations on IoT-based CPS prototype

Design/methodology/approach – The design research method, case study, emulation experiment method, and cost-benefit analysis are applied in this research. An IoT-based CPS architecture framework is proposed, and followed by the development of prototype system and testbed platform. Then, the emulation and experimental evaluation of IoT-based CPS are conducted on the testbed, and the experimental results are analyzed.

Findings – The emulation experiment results show that the proposed IoT-based CPS outperforms current barcode-based system regarding labor cost, efficiency, and operational adaptiveness. The evaluation of the IoT-based CPS prototype indicates significant improvements in PL tasks and reduced part inventory under a dynamic changing shop-floor environment.

Practical implications –The case study shows that the proposed architecture framework and prototype system can be applied to many discrete manufacturing industries, such as automobile, airplane, bicycle, home appliance, and electronics.

Originality/value –The proposed IoT-based CPS is among the first to address the need to integrate IoT and CPS for PL applications, and to conduct experimental evaluations and cost-benefit analysis of adopting IoT-based CPS for PL. This paper also contributes to the IoT research by using diverse research methods to offer broader insights into understanding IoT and CPS.

Keywords: Internet of Things (IoT), RFID, Production logistics, Cyber-Physical System (CPS), Emulation

Article Type: Research paper

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1. Introduction

Enterprises around the world are facing increasingly severe global competition, the shorter life cycle of new products, and changing customer demands. Therefore, they must transform their business operations to provide greater product variety and customization through flexibility and quick responsiveness, and also to remove the data latency, analysis latency, as well as decision latency as much as possible (Hackathorn 2003). Mass customization often requires firms to manufacture and deliver customer-specific products or services with the same price and efficiency as mass-produced products. In response to the new business model, they must adapt new information systems that can manage dynamic manufacturing activities and take immediate action to resolve any events that disrupt production or cause customer dissatisfaction (Byrd *et al.,* 2006). Coupling mass customization, just in time (JIT), and lean production with real-time business intelligence will enable a firm to compete in today's hyper competition environment (Du *et al.,* 2006). In other words, firms must re-engineer their current business practices to a real-time enterprise (RTE) operational model, which uses up-to-date information to eliminate business process delays (Kopitsch 2005). However, in the mass customization environment, the execution process of a production system is frequently disrupted by internal and external dynamics, such as equipment failure and changing customer orders (Qu *et al.,* 2016). The term production logistics (PL) describes these execution processes as logistics activities related to material transfer between production stages and PL often accounts for nearly 95% execution time of the entire manufacturing process (Qu *et al.,* 2016). To effectively employ mass customization and JIT production for RTE models, auto-ID methods are required for near real-time process control (Hansen and Gillert 2008). Many manufacturing firms already adopted auto-ID to manage their PL activities. The enabling technologies for auto-ID that attracted the most attention in recent years include Radio Frequency Identification (RFID) and Internet of Things (IoT). More specifically, IoT extends into our everyday lives through a wireless network of uniquely identifiable objects and forms a global infrastructure of networked physical objects (Welbourne *et al.,* 2009). This article (part B of the research) extended the implementation architecture proposed in Part A of this research. Part A of the research proposed an implementation architecture employing IoT technologies and comprising one IoT cloud and several iNodes, where each iNode manages multiple IoT devices We called the proposed implementation architecture an IoT-based CPS for PL and supply chain applications. Therefore, this aritcle is clearly link to Part A of this research.

IoT technology has been adopted by a wide range of industries in both indoor assets tracking (Thiesse *et al.,* 2006; Zhang *et al.,* 2007; Wang *et al.,* 2010) and outdoor assets tracking (Choi *et al.,* 2012). Recent studies also show that integrating IoT technology, such as RFID, in shop floor operations can greatly optimize and improve manufacturing and PL operations (Qiu 2007, Zhou *et al.,* 2007; Huang *et al.,* 2008; Ruey-Shun *et al.,* 2008; Wang *et al.,* 2012; Zhong *et al.,* 2013). The basic infrastructure of IoT consists of Electronic Product Code (EPC) and EPCglobal network (Thiesse *et al.,* 2009; Yan and Huang 2009), which provide a flexible and scalable information system architecture for implementing a range of applications, such as anti-counterfeit (Kwok *et al.,* 2010) and information sharing (Yan *et al.,* 2016). To fully realize the potential benefits of IoT technology, firms must adopt a new IT infrastructure that can better track and manage a large volume of distributed objects within their organizations and beyond. As we are moving towards the world of IoT, millions of embedded devices and industrial machines empowered with Internet technologies will be able to communicate, collaborate, and offer their functionality as a machine to machine (M2M) service (Karnouskos *et al.,* 2009). A device-to-business integration infrastructure is also required to manage dynamic business processes in the shop-floor environment (Karnouskos *et al.,* 2007).

Interacting with objects/things is the inherent nature of IoT systems, implying that IoT systems must relate and handle both physical and cyber worlds together. Hence Cyber-Physical Systems (CPSs) are introduced to bridge the gap between the physical and digital divide in IoT systems. PL involves many manufacturing and logistics activities beyond the four walls of a company and includes many supply chain partners. These PL activities are supported by many resources, including CNC machines, robots, conveyors, operators, and all kinds of sensors to facilitate the smooth operation of PL tasks. Thus PL must integrate production resources and activities across the entire manufacturing supply chain, and the integration poses a great challenge to PL information systems. The CPS shows the promise to integrate these activities and resources by synchronizing information between cyber and physical worlds and sharing production information between different stakeholders at different locations across a distributed and collaborative supply chain (Wang *et al.,* 2015). CPS must also integrate with IoT, cloud computing, and many other information technologies y to support PL activities in a diverse environment. The physical system of CPS includes sensors, actuators, and processing hardware while computational part of CPS comprises of software modules (Verl *et al.,* 2012). A CPS can use sensors and actuators to collect information about the physical operations in real-time and conduct intelligent control over physical systems to adapt to changing conditions and environment (Lin *et al.,* 2010; Verl *et al.,* 2012). In other words, CPSs monitor and synchronize all factory information between the physical world of shop floor and the cyber computational space (Lee *et al.,* 2015). Therefore, CPSs provide vital support for managing PL in an IoT environment. CPSs are amalgamations of computation and physical processes, which entail the necessity to study the joint dynamics of computers, software, networks, and physical processes for CPSs (Derler *et al.,* 2012). One major goal of CPS for Industry 4.0 is to integrate the physical world of shop floor with cyberspace so that fully interconnected machines and information systems can intelligently collaborate toward a common goal.

In real PL environment, it is very difficult to ensure that physical world in the factory shop floor aligning perfectly with the world model in cyberspace because of the large uncertainties of PL tasks in the real world. Thus the vertical integration CPS and IoT devices such as robots is critical for the successful application of CPS in PL (Krueger *et al.,* 2016). However, developing CPS or IoT systems for complex and harsh manufacturing environment is non-trivial as they require complex event processing (Wu *et al.,* 2010) and cross-layer system integration (Chang and Wang 2010; Bi *et al.,* 2014; Wang 2014). The system requirement for CPS is quite abstract thus cross-layer system integration architecture for CPS must be addressed (Lee *et al.,* 2015). Many CPS has a decentralized structure, and the deployment of distributed CPS in the industrial environment is also a very challenging endeavor (Leitão *et al.,* 2015). Monostori *et al.* (2016) also highlighted various R&D challenges in realizing CPS. Leitão *et al.* (2015) categorized CPS challenges in six areas- CPS Capabilities, CPS Management, CPS Engineering, CPS Ecosystems, CPS Infrastructures, and CPS Information Systems. Detailed discussions can refer to their works.

As 95% of execution time arise from PL tasks in manufacturing (Qu *et al*., 2016), studying the impact of IoT-based CPS on PL and evaluating its performance are undoubtedly essential to many manufacturing industries. However, until recently, few research activities (Lewandowski *et al*., 2013; Klötzer *et al*., 2015; Akanmu and Anumba, 2015; Krueger *et al*., 2016) have been undertaken to investigate CPS in PL and supply chain. On the other hand, the cost concern of an IoT-based CPS investment might become the main barrier to many manufacturers with tight profit margins (Wang *et al*., 2015). In that respect, evaluation is vital to many decision makers before adopting CPS. The evaluation might include software simulation, lab emulation with the implementation of a prototype system, and cost and benefit analysis of technology adoption. For example, Akanmu and Anumba (2015) developed prototypes to demonstrate key aspects of CPS and evaluated the CPS using a focus group comprising potential end users of the developed CPS. Nevertheless, using numerical examples and analysis to examine the costs and benefits associated with CPS implementation is still absent in published research articles.

In light of the above discussion about the importance of CPS in PL applications, the challenges facing CPS, and the lack of studies conducted in this area, three research questions were proposed to address these research gaps: 1) What is the system architecture of IoT-based CPS for PL? 2) How does IoT-based CPS relate to PL and manufacturing supply chain applications? 3) How to evaluate an IoT-based CPS before adopting the technology. To answer the three research questions, we propose three research objectives. The first objective is to present an IoT-based CPS architecture framework to facilitate the integration of IoT and CPS. The second objective is to implement an IoT-based CPS prototype based on the architecture framework for a PL application scenario of in a case study. Finally, the third objective is to devise evaluation methods and conduct experimental evaluations on IoT-based CPS prototype.

The focus of this research is on the CPS application in PL and supply chain application domain and thus we emphasis on the integration of RFID and CPS. Hence, our study is different from other studies in CPS regarding application domain. Unlike most CPS studies, we proposed in this paper a comprehensive evaluation method to facilitate the cost-benefit analysis of adopting IoT-based CPS, which is absent in most published CPS articles. From a manufacturing supply chain perspective, this study concerns not only the application of IoT-based CPS in PL within the boundary of a manufacturer but also addresses the communication and coordination mechanism between the manufacturer firm and its supply chain partners. For example, we designed and developed a CPS-based inter-firm adaptive component replenishment on our IoT-based CPS testbed platform and evaluated the performance of the mechanism regarding part inventory management in this article.

The remainder of the paper is organized as follows. Section 2 proposed an architecture framework for the IoT-based CPS. Section 3 presents a case study for this research. Section 4 describes the design and development of a CPS prototype and an emulation testbed. Section 5 discusses an experimental evaluation of IoT-based CPS with the testbed, and finally, Section 6 gives implications and conclusions.

2. A framework for IoT-based CPS in PL and supply chain applications

This section first reviews briefly previous works related to system architecture of CPS, then we proposes a framework for IoT-based CPS applied in PL and supply chain applications and describe the components of the framework in detail.

2.1 Foundations for CPS architecture

CPS can facilitate context- and situation-aware control based on the multichannel data communications between low-level sensors/actuators and high-level decision-making systems (Wang, *et al.,* 2015). The context-awareness of CPS can be manifested by the feedback looping mechanism built in CPS where physical processes affect computation at cyberspace, and the results of cyber computing can affect physical processes as a supervisory control, making CPS a self-adaptive system (Karnouskos *et al.,* 2007). To manage the pervasiveness of IoT-enabled objects in factories and support adaptive control of dynamic mass customization manufacturing processes, we must endow CPS-enabled devices or machines with the sensing capability to interact with the IoT-enabled objects and to take actions accordingly. These devices can be considered as a set of intelligent system entities which act like a conglomerate of autonomous, intelligent, pro-active, fault-tolerant and reusable units (Colombo and Karnouskos, 2009). M2M communications will take place among those networked CPS devices and industrial systems. Traditional centralized control algorithms will find it difficult to harness a large number of distributed objects interacting at any time, any place. One feasible solution is to endow M2M devices with a necessary dose of autonomy and use software agents for device control and management to achieve autonomous capability (Mišura 2013; Barenji *et al.,* 2014). In that respect, CPS can be modeled as a multi-agent system, where each agent is an autonomous unit capable of managing resources within its local scope (Lin *et al.,* 2010).

To design CPSs, Lee *et al.,* (2015) proposed a 5C level CPS architecture for Industry 4.0-based production systems. The 5C level includes (Smart) Connection, (Data-to-Information) Conversion, Cyber, Cognition, and Configuration. Other new IT framework, such as the Fog computing architecture, is proposed to design a large-scale, geographically distributed data-driven CPS for manufacturing applications (Wu *et al.,* 2016). A manufacturing execution system built on CPS can be seen as a Cyber-Physical Production System (CPPS). The CPPS has recently become an important research focus, especially in the development of CPS for manufacturing (Verl *et al.,* 2012; Monostori 2014; Lee *et al.,* 2015; Wang *et al.,* 2015; Kerpen *et al.,* 2016; Wu *et al.,* 2016). CPPS consist of autonomous and cooperative entities that are connected within and across all levels of production activities, extending from machine operation, process control, up to entire production and logistics networks (Monostori *et al.,* 2016). Thus, Monostori *et al.,* (2016) have identified three main characteristics underlying CPPS as intelligence (smartness), connectedness, and responsiveness. The three underlying CPPS characteristics were embraced in our proposed CPS architecture framework discussed in the next section and also applied in developing the IoT-based CPS testbed platform in later sections.

2.2 Architecture framework for IoT-based CPS

Based on the CPS reference design given in Wu *et al.,* (2016), Lee *et al.,* (2015), and the previous work of this research (Tu *et al.,* 2009), the system architecture framework of the IoT-based CPS is proposed, as depicted in Figure 1. The architecture framework integrated software components in the cyberspace and IoT devices in the physical environment. From the perspective of fog-enabled infrastructure architecture (Stojmenovic 2014; Wu *et al.,* 2016), an intelligent IoT edge computing node (termed as iNode) in our framework is similar to a gateway device or a smart grid run on a network edge device. Referring to the 5C architecture (Lee *et al.,* 2015) on information processing and software design aspects of CPS, the connection and conversion levels of 5C can relate to our data capturing and pre-processing modules, such as RFID or sensor middleware in iNode and enterprise integration module, and shop floor data capturing module in IoT cloud. The cyber level of 5C covers most of the function modules in IoT cloud, for instance, the cognition level of 5C is similar to our iNode reasoning module, and the control aspect in the configure level of 5C is similar to that of iNode control module. Compared to our previous work (Tu *et al.,* 2009), several software modules in the iNode have been improved to reflect the new design concept of CPS in an Industrial 4.0 context, while most of the hardware components of the system remain the same.

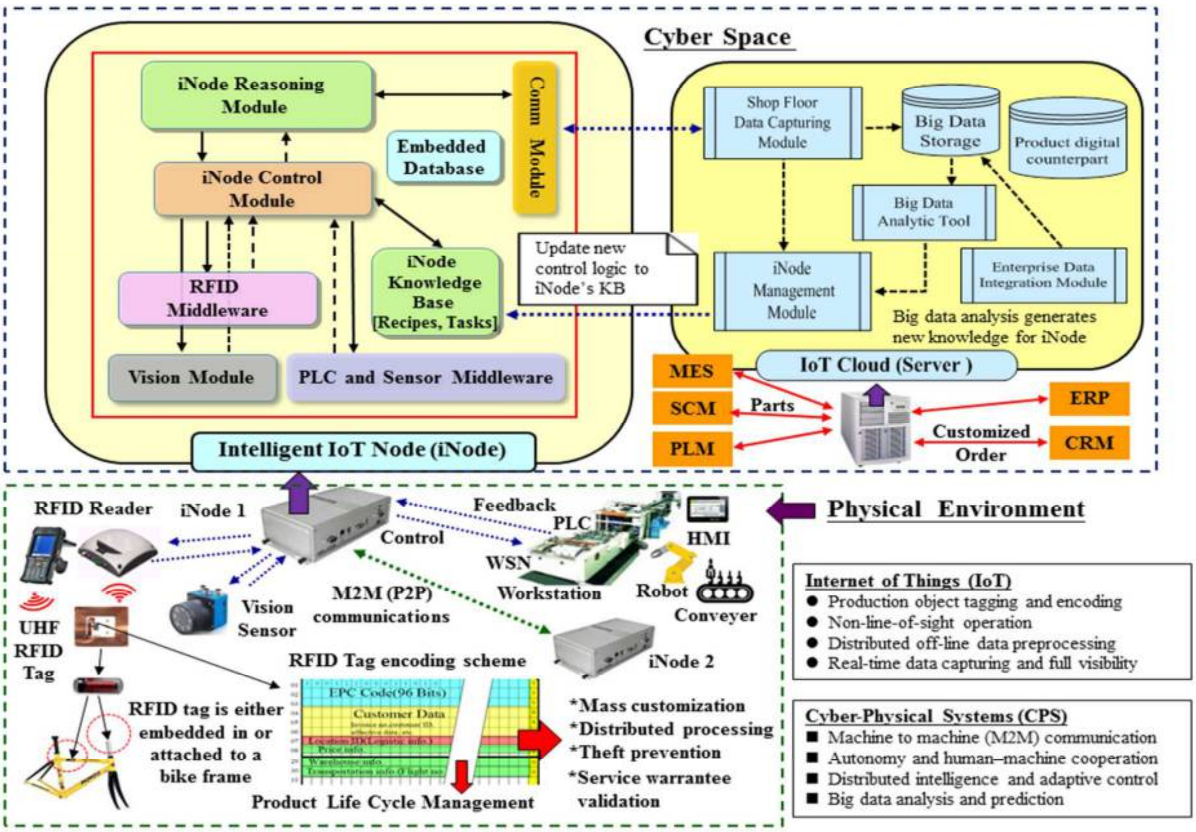

Figure 1. Architecture framework of the proposed IoT-based CPS for PL and supply chain applications

The main IoT technology used in our proposed system is UHF RFID. As illustrated in Figure 1, an IoT-based PL system will include passive UHF RFID tags, fixed and handheld UHF RFID readers, vision sensors, robots, conveyors, human-machine interface (HMI), and intelligent IoT nodes managing and interfacing with production machines and the aforementioned IoT-enabled objects. The iNode is also part of the CPS and will be discussed later. Depending on Tbike's business considerations, a passive UHF RFID tag can be directly embedded in a bicycle frame, or a device that locked onto the frame, or in a lock mount that attached to the frame. Customer and production data can be written onto RFID tag's memory based on the tag encoding scheme of Tbike during tag initialization stage. The IoT technology employed in the PL features object tagging and encoding, non-line-of-sight operations, real-time visibility, and traceability, and distributed off-line processing. These features can facilitate IoT-based business processes and service models as further explicated below:

- *Mass customization*: Each customer can order an electric bicycle with different configurations and part options. The unique manufacturing specification for each customer can be written onto RFID tag's memory. Thus each unique production method encoded in the tagged workpiece can be read by the RFID reader and being processed accordingly. The IoT system enables Tbike to custom make each bicycle in large quantity on its hybrid production line.
- *Distributed processing*: The IoT technology employed in this study is a fully distributed architecture where each iNode has autonomous control over its own behavior about performing production tasks. Since the production code can be encoded in the RFID tag at the initialization stage, iNode can correctly choose and execute a production method based on the code of the embedded tag on the production line without connecting and retrieve information from a server or cloud system. The distributed off-line processing capability of IoT system makes the manufacturing system more reliable and robust as it can avoid a single point of failure and can also be scaled easily with increased production processes and product types for hybrid production lines.
- *Theft prevention*: If RFID is embedded onto a bicycle frame, a stolen or lost bicycle would be much easier to be identified and returned to the owner swiftly. This could reduce bicycle theft and increase the chance of stolen bicycle recovery.
- *After-sale service and warranty validation*: With the RFID tag embedded on each electric bicycle, the bicycle shops can easily validate warranty by reading the data encoded in the tag without the need to retrieve information from elsewhere.
- *Product life cycle management*: As passive UHF RFID supports both reading and writing operations, a tagged electric bicycle does not only store product information, after-sale service information, such as maintenance or repair codes can also be recorded. These service records can also be updated in the IoT cloud system if necessary. IoT technology enabled each bicycle to carry its product life cycle information, which can be used to support and enhance customer service at different stages of product life cycle.

In our proposed CPS architecture, the physical environment comprises of three categories of things as described below:

(1) Tagged objects: Tagged objects may include WIP, finished product, and parts. There are many object tagging technologies, such as a 2D barcode, HF RFID, UHF RFID, etc. However, this research only evaluates UHF RFID.

(2) IoT devices: RFID readers, vision sensors, iNodes, and various types of sensors for collecting machine or environment data are considered as part of IoT device family.

(3) Production-related equipment and tools: Commonly seen equipment and tools in a factory belonging to this category, for example, CNC machines, industrial robots, conveyor, and HMI.

Our proposed CPS architecture framework consists of an embedded system called iNode and IoT cloud. The iNode is part of CPS, serves as an edge computing device built with software agents to support multiple tasks in a PL environment. Our proposed CPS framework for PL has several characteristics, including M2M communication, autonomy and human-machine cooperation, endpoint intelligence and adaptiveness, and big data analysis and prediction, as shown in Figure 1. As a key part of CPS in a smart factory environment, iNode can communicate with other iNodes, e.g. RFID readers, workstations, transportation devices such as conveyors, and software modules in the cloud. Thus, we define five types of M2M communication channel in the proposed CPS; they are (1) iNode to iNode, (2) iNode to RFID Reader, (3) iNode to Production Machine, (4) iNode to Device, and (5) iNode to IoT Cloud. The M2M communication can take place on either wireless or wired networks. Any reliable industrial computer can serve as a hardware platform for iNode. The software modules in the node will be devised to endow iNode some autonomy to control its own behavior and to communicate with other IoT devices. In this research, we designed iNode to demonstrate a new CPS-based autonomous control paradigm in a PL environment. An iNode can be integrated with HMI upon which touchscreen-based user interface applications or augmented reality (AR) applications can be developed to support human-machine cooperation. As an autonomous entity, iNode can convert various sensor data from RFID, PLC signal, vision, and other environment sensor data to operational metadata and exert its intelligent control over a workstation or a production cell with machines and robots, showing the characteristics of end point intelligence in our proposed CPS framework. Furthermore, an iNode can also communicate with its neighboring iNodes to coordinate production tasks under different operational policies and environmental changes, demonstrating adaptive control capability of iNode. Finally, IoT cloud constantly monitors activities of iNodes, collects and stores information (operational metadata) from iNodes, analyzes the information, and updates business rules or control logics to iNodes. At the same time, IoT cloud can also provide management console which allows the system administrator to configure iNode.

As mentioned above, our proposed IoT-based CPS system architecture framework consists of two parts, the first part of the framework is the embedded system iNode and the second part is the IoT cloud. The constituents of each component are described below:

(A) Intelligent IoT Node (iNode): The software architecture of iNode adopt agent design paradigm and comprises the following modules.

(1) *iNode Reasoning Module:* The reasoning module receives operational metadata from the iNode control module and task-related messages from neighboring iNodes and IoT Cloud. Based on this information, iNode is aware of the current situation of the physical world, and thus make an informed decision in picking the next goal to act in response to environmental changes.

(2) *iNode Control Module*: The control module receives instructions from reasoning module and collects data from physical world through RFID middleware, vision module, PLC and sensor middleware and converts them into operational metadata. Based on the operational metadata and business rules, the control module selects executable plans from the iNode knowledge base and executes the control logic encoded in a plan. These executable plans represent production recipe or any specific task related to a PL process.

(3) *RFID Middleware*: When RFID antenna's radiation field detects tagged objects, the RFID reader will receive the RF signals back from passive UHF RFID tags. These signals could represent one or more object IDs, which must be filtered by a RFID middleware to make these data usable. In our framework, we require that, aside from data filtering, RFID middleware must also convert the filtered raw data into object event data, such as EPCIS event data, which includes space, time, and business context information in addition to object ID. In our framework, RFID data is handled separately from other sensors, such as vibration or humidity sensors, because RFID data might contain state information while other sensor data are stateless.

(4) *Vision Module*: Many manufacturing firms have been using various types of cameras to perform video analytics to improve production process control and quality monitoring directly on the

production line, especially for the quality inspection. Thus, embedded video analytics processing with the camera should be integrated into the IoT-based CPS. The video analytics capability should be able to decipher the video analytics and convert the information into contextualized events operational metadata. In our case study, Tbike may consider using video analytics to monitor the painting quality of its bicycle frame in the painting process.

(5) *PLC and Sensor Middleware*: In addition to RFID middleware, our CPS framework suggests that a PLC and sensor middleware is necessary to support the iNode's communication and interaction with PLC controller and machine related wired or wireless sensor networks (other than RFID and vision sensors). PLC and sensor middleware must include a module to convert raw PLC/sensor data into operational metadata.

(6) *iNode Knowledge Base*: The knowledge base (KB) of iNode stores business rules and control logics. Different control logics are grouped into sets of executable plans, representing production recipes or tasks.

(7) *Embedded Database*: Since the iNode can operate in an offline processing mode, an embedded database is required in our framework to support temporary data cache. The cached data will later be scheduled to export to IoT cloud and synchronize with cloud storage.

(B) IoT Cloud:

(1) *Shop Floor Data Capturing Module*: Shop floor data capturing is highly coupled with a manufacturing execution system (MES) system, which is an enterprise PL system designed for tracking WIP and parts and managing the production process. In our framework, PL data will be collected from iNodes and stored in a big data storage module; some of these data can either be stored on IoT cloud or directly in the MES database. However, most of the sensor data in the framework, e.g. from the RFID and vision sensors, are advised to be stored in the big data storage of IoT cloud.

(2) *Data Storage*: The data storage of IoT cloud should contain both structured data (such as SQL) and unstructured data (e.g. text, log, and image). Current mainstream database systems, such as Oracle database, support both SQL and NoSQL data storage. Logically, we divide the database into two groups. The product digital counterpart stores life cycle information for each manufactured bicycle, including production pedigree. Data written in the RFID tag must synchronize with product digital counterpart within a given period. The rest of data are contained in the big data storage, including metadata, sensor data, and PL related transaction data.

(3) *Big Data Analytic Tool*: Big data analysis in our framework is conducted offline. Various available commercial statistical and data mining software or open source programming languages, such as R Language, can be considered as big data analytic tools. The offline big data analysis first generates new knowledge, which will then be converted into business rules and control logics, and finally, updates to the KB of iNodes deployed on the factory floor.

(4) *iNode Management Module*: This module provides an iNode Management console for the system configuration, business rules configuration, iNode monitoring, and knowledge updating for iNodes. This module facilitates the dispatching of production methods (plans) to an iNode's KB repository.

(5) *Enterprise Data Integration Module*: The purpose of our proposed CPS is to better manage the PL. Thus this module is designed to integrate with the enterprise information system about PL. This module uses ETL (extraction, transformation, and loading) procedures to perform bi-directional data transformation between enterprise systems and the IoT-based CPS. In the broad sense, enterprise resource planning (ERP), customer relationship management (CRM), manufacturing execution system (MES), supply chain management (SCM), and product lifecycle management (PLM) are all associated with PL.

3. Case study

Electric bicycles are becoming increasingly popular in many countries, and many firms in this industry have tried to evaluate and adopt new technology such as IoT and CPS to improve their PL operations and supply chain management. Thus, a case study regarding an electric bicycle manufacturer was used to support the evaluation of our proposed IoT-based CPS. The case study examines a large Taiwanese bicycle firm called Tbike (a fictitious name for anonymity purposes) specialized in electric sports bicycles. The manufacturer has expressed high interests in applying IoT technology such as RFID in its manufacturing. Figure 2 illustrates the scenario where the RFID tagging being integrated into the Tbike's production and logistics processes. Tbike has adopted the Just-in-time (JIT) or lean production method to build their bicycle models in mass customization mode.

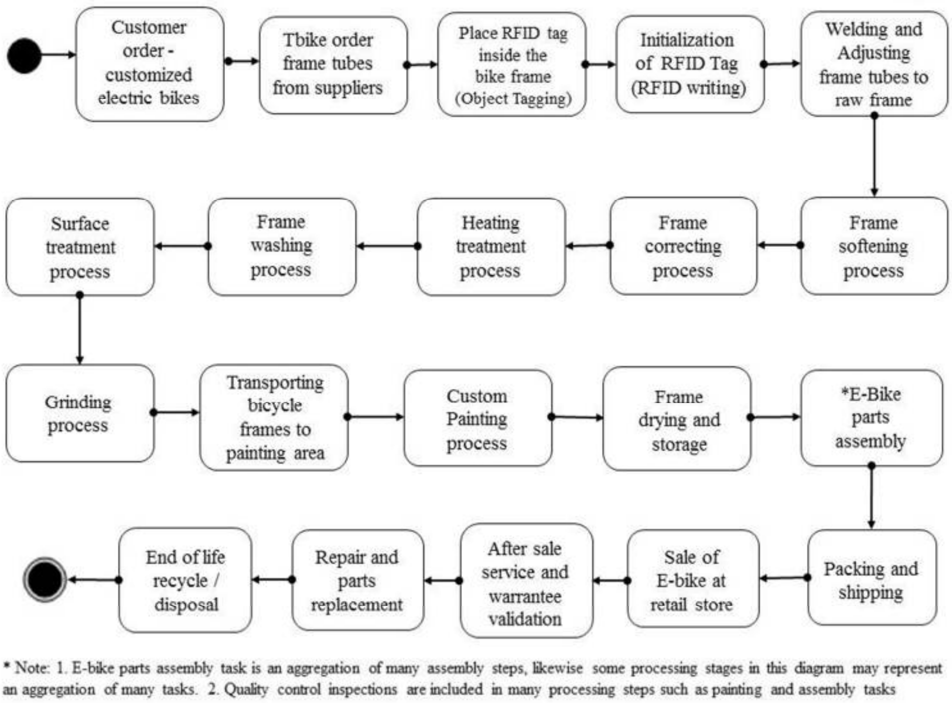

Figure 2. Production processes of electric bicycle manufacturing

Tbike currently uses paper travelers with barcode labels to track and identify thousands of frames moving around the plant facility each day. Barcode labels were also used to direct pickers to the places where parts are located. However, tracking all frames and parts and acquiring up-to-date inventory and work-in-process (WIP) information for Tbike are still considered as daunting tasks. Tbike suffers from excessive in workforce requirements and operational data latency and inaccuracy in performing these tasks. Incorrect and delayed information of WIP and the consumption of critical parts could affect the effectiveness of JIT operations and inventory management of parts of Tbike, especially for its mass customization production lines. Many of Tbike's plants in Taiwan are aimed at high-end, high-performance electric bicycles. To meet intense competition in the market, Tbike allows customers to choose a variant of products, including model type, frame size, color, and other features. Therefore, the inefficiency above will adversely affect Tbike's production and customer service quality. To help Tbike enhance competitiveness, we will investigate how IoT technology and CPS can help Tbike overcome these challenges and evaluate the potential benefits of adopting our proposed IoT-based CPS for PL.

The research focus of this study is about the application of CPS in PL. Thus, the case we selected must support our research goal and provide a good application scenario for our study. As described in the above discussion, one major objective of the electronic bike manufacturer (Tbike) was to improve its PL operations with the help of IoT technology and CPS. This case also addressed some important traits that align with our research interest, including mass customization, inventory management of parts, and lean production method. The above discussion clearly justified the selection of the case for this research.

4. Design and implementation of CPS prototype and emulation testbed

An emulation has been used in the study of IoT-based systems, e.g. in RFID system and mobile ad-hoc networks (Tu *et al.,* 2009; Beuran *et al.,* 2010). It is a technique often used to close the gap between simulation experiments and real-world trials. In comparison to simulation, experimental results from emulation are more useful in practice since emulation uses real components (Tu *et al.,* 2009). The emulation platform of this study integrated several prototypes of hardware and software units to build an automated production and logistics control testbed system based on the IoT-based CPS system architecture described above. The emulation testbed developed for IoT-based CPS is illustrated in Figure 3. The testbed will emulate a portion of Tbike's production line. In the testbed setting, iNode 1 has dual roles for emulation experiment. The first role is to emulate a painting workstation, and the other is for a supplier's part production factory, in this case producing e-bicycle battery for Tbike.

Depending on the implementation requirements, each iNode can control a single machine, a workstation, or a manufacturing cell which may include several processing machines. The software modules of an iNode are shown in Figure 1, which have been described in the previous section. The vision sensor and vision module are not considered in this phase of research and thus not included in the prototype system. Since our testbed platform uses Lego components to emulate PL environment, the PLC, and sensor module were developed only for interacting with Lego controllers, including collecting Lego sensor data and issue a command to Lego controller to activate Lego workstation and Lego conveyor. Figures 4 and 5 illustrate the operations of the testbed. The modules implemented in IoT cloud in this study include the shop floor data capturing module, iNode Management module, and big data storage. Data are stored in a relational database using MS SQL server. The remaining modules such big data analytic tool and enterprise integration module, as shown in Figure 1, will be implemented in the next phase of research. In the physical testbed environment, iNode is an intelligent IoT edge computing node. From the perspective of cyberspace, iNode can be seen as an agent-based system with software agents endowed with pre-defined goals. These agents reside on an embedded device and can communicate with each other. They can have their image copies stored on the IoT cloud. The IoT cloud provides a remote iNode Management module to assist iNode management tasks, such as iNode creation, registry, and business logic creation. The user interface of iNode management module is shown in Figure 6. The CPS prototype developed here is a critical part of our proposed IoT-based PL and supply chain system described in Part1 of this research (presented in the preceding issue of this journal). In Part 1of this study, we have proposed an IoT-based manufacturing supply chain network architecture and outlined the approach to integrate CPS into that architecture. Thus, the design of M2M interaction scheme for the IoT-based CPS on the testbed is based on the IoT-aware process modeling approach proposed in Part 1. Each iNode device in the testbed manages one major manufacturing or PL process, where each process corresponds to an IoT-aware process described in Part 1 of this research. Nevertheless, an iNode can expand to manage multiple processes, for instance, an iNode in a production cell can handle a conveyor and two robots. These IoT-aware processes represent production recipes or specific tasks stored in the iNode knowledge base as executable plans that iNode control module can use them to perform manufacturing or PL tasks. In section 5.2, we will further discuss how CPS works in an IoT-based adaptive manufacturing supply chain network to achieve M2M coordination with experimental evaluation using this testbed platform.

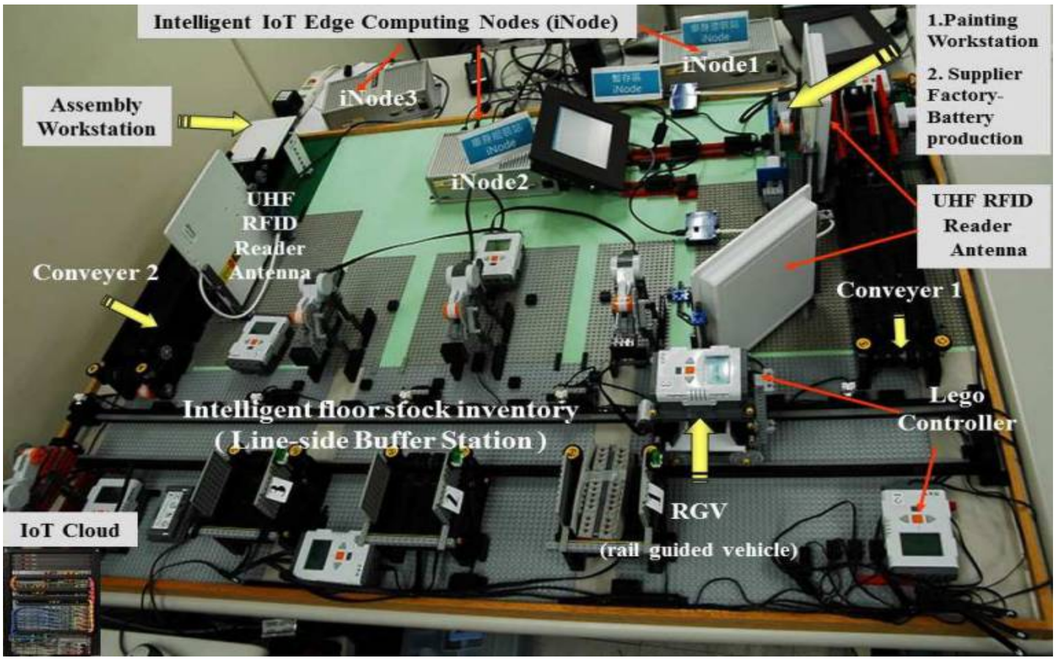

Figure 3. The iNode prototype and the Lego emulation testbed

5. Experimental evaluation of IoT-based CPS

As IoT and CPS technologies have become a vital part of Industry 4.0 and smart factory, manufacturing enterprises around the world are exploring their practical applications by conducting pilot research projects. To investigate the potential impact of these new technologies on enterprises, we conducted emulation experiments to evaluate the performance and benefits of adopting an IoT-based CPS for PL management. The emulation was divided into two parts. The first part evaluates the operational efficiency of PL tasks. The two main features being evaluated are IoT's non-line-of-sight technology (using UHF RFID) and iNode-enabled shop floor workstation. An emulation testbed for IoT-based CPS was developed and compared with Tbike's current run card and barcode system.

The second part evaluates the distributed intelligent IoT-based CPS, assuming that a firm has already adopted non-line-of-sight technology such as UHF RFID. This evaluation highlights the advanced features of the IoT-based CPS regarding the distributed intelligence of iNode and M2M coordination among iNodes. The main feature evaluated was an adaptive inventory control mechanism implemented on iNode to manage line-side part inventory. We will compare the performance between two models: one employing M2M distributed intelligence and the other one without such technology. Both IoT and M2M distributed intelligence are part of our proposed IoT-based CPS. However, each technology tackles different problems facing a production enterprise like Tbike. We need to distinguish them regarding their performance evaluation. IoT technology is aimed at automating operation processes regarding identification, tracking and tracing of products within a company and across the entire supply chain, resulting in a great saving of time and labor costs, and improved operational efficiency. M2M's distributed intelligence, on the other hand, is adaptive to changing environments and can take proactive actions to handle disruptive events from the operation. In other words, it can improve the firm's operational adaptiveness and also help transform an enterprise into an agile and lean organization.

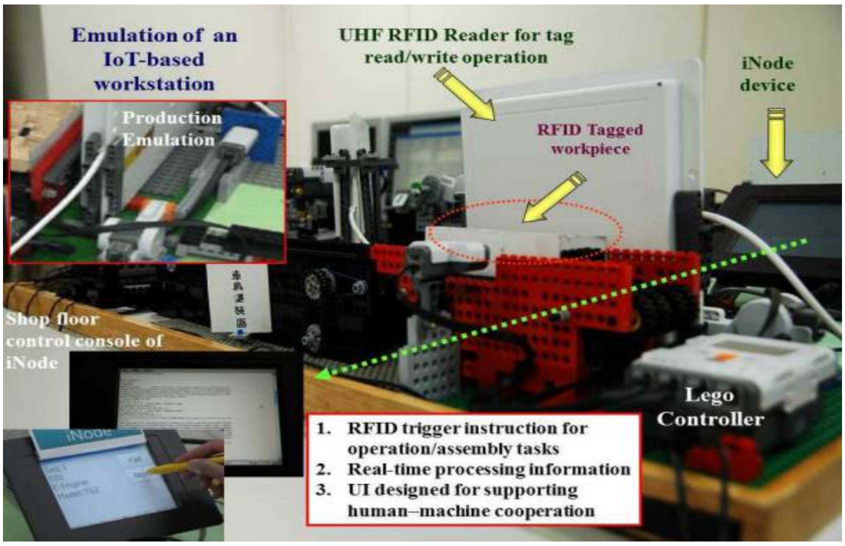

Figure 4. Emulation of iNode-enabled shop floor workstation

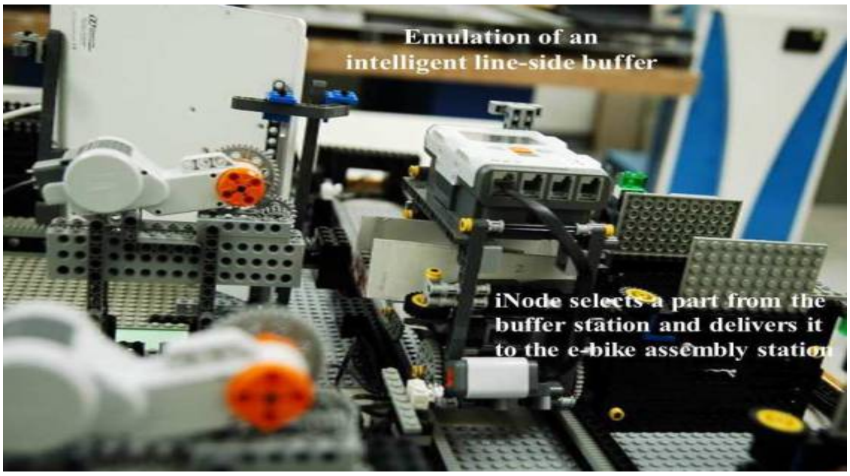

Figure 5. Emulation of iNode-enabled intelligent part buffer station

Figure 6. iNode management module

5.1 Evaluation of operational efficiency for PL tasks

The testbed emulates operations at the Tbike's shop floor. The facility layout is divided into three parts: one section for queuing and two sections for manufacturing tasks, as presented in Figure 3. When a production manager issues work orders to the iNode, a workpiece (emulating a bicycle frame) attached with a passive UHF RFID tag preloading with frame ID, customer ID, and work order information is then picked up for painting. The UHF RFID technology enables non-line-of-sight (NLOS) operations for IoT-based CPS in PL. Once detecting a RFID tagged workpiece on its working place, a workstation invokes and executes a sequence of production or processing events. Lab operators can easily work on the shop floor control console and obtain real-time information about manufacturing status as shown in Figure 4. The system components of assembly workstation are similar to that of painting workstation. Lie between the painting and assembly workstation is the intelligent buffer station as shown in Figure 5. This buffer station is a buffering zone storing painted bicycle frames. Since each frame has its corresponding work order specifying its expected shipping date required by Tbike's customers, the intelligent buffer station will always choose a frame with the highest priority and delivers that frame to the assembly workstation. Other lab operators can also access whereabouts and status information of all workpieces in real-time through the IoT cloud system. This emulation testbed shows that the proposed IoT-based CPS for Tbike can virtually eliminate the need to use paper-based run-card or manual barcode scanning in WIP tracking. The IoT-based CPS can also help Tbike achieve close to 100% visibility of WIP tracking in PL, which is not easy to achieve under current practices. This emulation testbed can be used to evaluate other similar manufacturing settings such as motorcycle and car production.

To keep track of thousands of bicycle frames, Tbike operators must spend time in barcode scanning. While this approach is inexpensive and simple to implement, it is hard to automate as the barcode is a line-of-sight technology. In Tbike, we identified three major shop floor activities related to PL as potential areas for improvement:

1) Barcode scanning of bicycle frame ID to initiate production tasks.
2) Barcode scanning of bicycle frame ID to associate with scanned component/part ID (for assembly processing steps).
3) Paper-based signing off on job completion.
4) Removing and reattaching paper-based barcode. This task must be performed for some batch processing of bicycle frames, such as softening and heating if paper-based barcode system is used. This task includes detaching the paper-based barcode from each bicycle frame before batch processing and reattaching the barcode to the correct frame after batch processing. This PL task is, therefore, labor intensive and is prone to error.

We term these shop floor activities as production logistic tasks (PLT) 1~4. The goal of the IoT-based CPS is to reduce or eliminate time and labor cost used to perform PLT, such as workpiece scan and sign-off tasks after critical part assembling.

RFID technology presents one of the best alternative options, bringing increased data capacity and the ability to read tags without line-of-sight. Therefore, one major perceived benefit of our proposed IoT system framework is the reduction/elimination of time spent on the manually scanning of bicycle frames and data entry of paper-based sign-offs. On the other hand, scan time saving also implies labor cost savings for Tbike. The fully automated data capturing operations of the proposed IoT-based CPS can thus both save time and reduce labor costs. Equation 5.1 shows a measuring scheme to estimate the time savings of scanning operation; the formula only considers the bike frames since Tbike only considers putting each RFID tag inside every bicycle frame, not including bicycle assembly parts at the current stage; barcodes are still used to label components/parts. Equation 5.2 is used to obtain time savings in terms of percentage change. The result of 5.1 can be converted to total working hours saved per day using Equation 5.3 and the labor cost savings per day with Equation 5.4. A final notice is that the following estimation does not consider the cost of implementing and maintaining an IoT system.

$$T_S = \sum_{Wi=1}^{n} (T_{NR} * B_{Wi} - T_R * / B_{Wi}) * Q \quad (5.1)$$

$$T_S\% = [\, T_S \;/\; (\sum_{Wi=1}^{n} T_{NR} * B_{Wi})*Q \,] * 100\% \quad (5.2)$$

$$T_{S\text{-}hr} = T_S / (60*60) \quad (5.3)$$

$$L_{CS} = [\, T_{NR}/(60*60) \,] * Awr \quad (5.4)$$

where

T_{NR}: average time to perform line-of-sight object scan without RFID for all PL tasks (seconds/per object)

T_R: average time to perform NLOS scan using RFID for all PL tasks (seconds/per object)

T_S: time savings for scanning using RFID (seconds/per day).

$T_S\%$: percent decrease in scan time

$T_{S\text{-}hr}$: working hours saved per day

L_{CS}: labor cost savings per day

Q: average quantity of bicycle being make per day in a factory

W_i: a processing station requiring the scan operation, such as assembly or packing workstations

B_{Wi}: the batch size of bicycle frames for each workstation. Most workstations process at least one frame ($B_{Wi} = 1$), while some workstations process more than one frame at a time ($B_{Wi} > 1$). For example, the softening process requires a batch processing of 10 to 12 frames simultaneously. Thus, the scan time must be divided by the batch size.

Awr: average hourly wage rate per worker

To justify the use of IoT-based CPS in PL operations, we evaluate the benefits and costs of adopting such system using Tbike's case in the following discussion.

(1) Evaluation of benefits - Reduction/elimination of time and labor cost used to perform PLT

Based on the information provided by Tbike, 24 major PL processes are selected for IoT performance evaluation along with other operation parameters. We assume that both fixed and handheld UHF RFID readers will be deployed for identification and tracking of bicycle frames and require an average of 1 second to read a passing object. The case of batch read has been included in Equation 5.1. Using Equations 5.1 to 5.4, the procedures of evaluating the improving effect from barcode scanning to RFID reading are elucidated in the following calculations. The following assumptions and parametric data are provided for performance evaluation:

(a) Assumptions:

1. The scope of evaluation processes ranging from welding to packing and shipping, with a total of 24 operations, including 12 major assembly tasks and 2 packing tasks that require performing PLT. We assume only the 24 workstations are required to be tracked for e-bicycle's PL.
2. All PL activities of the 24 operations have at least two PLTs, where 11 assembly tasks have all three PLTs.
3. Based on the field test, the task of RFID tagging and tag initialization take roughly the same time as barcode printing and labeling. Thus, RFID and barcode tagging steps are excluded from the evaluation.
4. In Tbike's case, the time taken to perform PLT 1~4 may vary with different production steps. To simplify the evaluation, we calculate an average processing time per unit of a bicycle for each PLT respectively.
5. We ignore other PL tasks and focus only the four previously defined PLTs in this research.

(b) Parametric data for evaluating Tbike's logistics operations:

- T_{NR} is 8, 12, 10, 30 seconds for PLT 1~4 respectively
- T_R is 1 second for PLT1~2, 2 seconds for PLT3 and 0 seconds for PLT4
- Q is set to 850 bicycles produced per factory per day
- *Awr* is set to an average of NT$ 200 per hour for a field operator
- The processing batch size B_{Wi} for softening, soak cleaning and heating processes are 12, 12, and 10 frames respectively. The rest of processes have a batch size of 1.
- There are three logistics scanning jobs to perform for packing and shipping processes, including the dispatching process after the final assembly, the final verification and packing process, and the truck loading process. Considering the two alternative tagging methods (embedded tag or reusable tag) that Tbike might adopt in the future, we only evaluate dispatching and packing processes in this case because only RFID embedded solution is applicable after packing stage.
- The T_{NR} for dispatching and packing processes are 10 and 25 seconds respectively. The packing is the most time consuming in this stage because it requires final verification of finish product against customer order before an e-bicycle being put into a container box and ship out of the factory. The verification takes only 1-second using IoT-based solution by reading the RFID tag attached to the bicycle.

There are many frame processing and part assembly steps in the electric bicycle production; we divide these production steps into three cases:

Case 1:
We evaluate frame processing steps from welding to frame drying, a total of 10 processes. Among them, seven processes require PLT1 and PLT3, and the remaining is batch processes. The batch processing tasks in this study include washing, heating, and softening processes; these batch processing tasks are required to perform PLT1, PLT3, and PLT4.
Substituting previously defined parametric data into the corresponding variables in the Equation 5.1 we get [(18-3)*7]*850 = 89,250 (seconds saved per day).
For the three batch processing tasks, we have
[(30*12)-(3/12)]*2*850 + [(30*10)–(3/10)]*1*850 = 866,320 (seconds saved per day).

Case 2:
We evaluate 12 bicycle assembly processes with Equation 5.1. All assembly tasks require PLT1~3.
[(30-3)*12]*850 = 275,400 (seconds saved per day).

Case 3:
We evaluate 2 packing related processes with equation 5.1. All packing related processes require PLT1 and PLT3.
[(10-3)*850] + [(25-3)*850] = 24,650 (seconds saved per day).

Summing up the results of above cases we got 1,255,620 seconds saved per day, which is about 349 working hours (Equations 5.3) for PL operations. On a 310 workday basis, Tbike can save 108,190 working hours per year, which is equivalent to NT$ 21,638,000 labor cost savings (Equation 5.4). No labor is required for NLOS tasks, the only line-of-sight task for IoT-based CPS in this study is PLT3 because Tbike prefers an operator to perform sign-off tasks on the control console of iNode. The labor cost of PLT3 can be calculated according to the data and the formula above. The net cost saving is thus equal to NT$ 21,638,000. Applying Equation 5.2, we obtain a 96% decrease in scan time. The results are summarized in Table 1.

(2) Evaluation of Cost - Building IoT-based CPS:

Table 1 evaluates only the quantifiable benefits from IoT-based CPS in Tbike's case. We like to treat the cost evaluation of RFID hardware and software investment separately since they tend to vary depending on alternative solutions. To evaluate the cost factor, we divide the entire system into three categories and assess each category separately:

- The cost of RFID readers:

We consider the RFID readers to be either fixed and handheld. A fixed reader can part with four antennas, and each antenna can be seen as a logical reader, we can call such combination a reader set. The cost of such industrial RFID reader set costs from NT$ 80,000 to NT$ 180,000. On the other hand, a handheld reader will cost around NT$ 100,000. Given the 24 processing steps evaluated above, we assume that all 22 production processes use fixed readers and the other two packing processes use handheld readers. Six reader sets are required to cover 22 production operations, and two handheld readers are required for packing tasks. If each fixed reader set costs about NT$ 120,000 and the handheld reader is NT$ 100,000, then it costs about NT$ 920,000 to acquire RFID readers. Based on experience, we set the lifespan of a reader set to 5 years. Thus the reader investment can be amortized over the five-year period, reducing the cost of ownership to NT$ 184,000 per year. In general, RFID readers can be considered as the fixed cost of an IoT system.

- The cost of RFID tagging:

The cost of RFID tags is the variable cost of an IoT system since the volume of tags is depending on the volume of products or parts in the factory. The cost of a passive Class 1 Gen 2 UHF RFID tag can range from NT$5 to over NT$200, depending on the tag's packing, user memory capacity, and most importantly the order volume of tags. Special packing for metal or heat resistance RFID tag could cost about 3 to 10 times that of normal packing tag. There are two options for evaluating the cost of RFID tags. The first case is that RFID tags are reusable, which is quite often seen in manufacturing firms. The second one is the non-reusable case where a firm may wish to implant a RFID tag inside a product permanently. The two alternatives will have a significant difference regarding variable cost for an IoT system. Both the price and the profit margin of an e-bicycle is much higher than that of a traditional bicycle. For example, in the market, many e-bicycles are priced between NT$47,000 and NT$157,000, and thus a tag costs about NT$300 is considered trivial. Therefore, in this study, we propose three RFID tagging strategies. Tbike could put the three tagging alternatives into consideration, and we evaluate these strategies separately in the following discussion.

Strategy 1 (Reusable RFID Tagging):

A UHF Class 1 Gen 2 RFID tag with 10-year/100,000 writes cycle memory endurance is chosen for this evaluation. The unit price of such tag is estimated at NT$300. We can obtain the total cost of product tagging by multiply the cost of the tag by the daily production volume in the reusable case. However, considering the variability of mass customization production mode of Tbike and the possible loss or damage of RFID tags, we set the tag volume to 1000. Thus, the yearly cost of product tagging is (300*1000)/10 = NT$30,000.

Strategy 2 (Embedded RFID Tagging):

There are several ways to embed RFID tags into e-bicycles. We can treat RFID tag as a key component of an e-bicycle and place the tag in various locations of a bicycle depending on the model of bicycle or business considerations. We could also embed the tag with other critical parts of e-bicycle, such as battery set. An embedded tag could become a vital IoT device for product life cycle management of e-bicycle, as illustrated in Figure 1. Following the previous example, the cost of RFID tagging is calculated as (850*300*310) = NT$79,050,000 (per year).

Strategy 3 (Hybrid Product Tagging):

This strategy tries to combine the advantages of both Strategies 1 and 2. To achieve the goal, we proposed a two-phase product tagging strategy where the reusable tag is applied in the first phase, the production phase, and the embedded "product tag" is applied after production in the second phase and permanently become part of an e-bicycle. This two-phase tagging strategy may greatly reduce the cost of RFID tagging as a firm could use specially packaged reusable RFID tags (usually expensive) for PL in a harsh manufacturing environment and apply less expensive general purpose RFID tag (costs about NT$ 10~50 per tag) after production. Based on this hybrid product tagging strategy, an extra RFID tag handling task must be performed to deal with tag swapping and tag data transformation and transfer. We will use Strategy 3 in our PL evaluation and only consider phase 1 scenario of the production phase tagging. Thus, the cost of phase 1 RFID tagging is the same as that of reusable RFID tagging strategy, which is about NT$ 30,000.

- The cost of IoT-based CPS:

The cost of developing in-house versus purchasing off-the-shelf for IoT-based CPS system varies. Unlike ERP systems, many IoT systems still require a high amount of customization even if purchased from a vendor. Therefore, it is not easy to find an off-the-shelf IoT solution that can fit Tbike's needs without customization effort. In this study, we only evaluate the in-house development cost. In our proposed solution, iNode devices can control at least one reader set and several production tools or machines. It is estimated to cost about 4 million NT dollars to build our proposed system for a single site e-bicycle factory. The development budget will include salaries of engineers (mainly software developers), system hardware costs (ex. industrial computers for iNode and a cloud server), software license fees, and some outsourced developing software modules, such as vision module. The IoT-based CPS system is estimated to run for at least eight years, and its development cost can be amortized over eight years period if all the production processes remain the same. The yearly cost of the system ownership is then reduced to NT$500,000. Adding the cost of RFID tagging (NT$30,000) and the cost of RFID readers (NT$184,000) to the estimated cost of IoT-based CPS, the total annual cost of ownership (TCO) for system's hardware and software will be NT$714,000.

We evaluate the improving effects of IoT-based CPS adoption by Tbike and summarize the evaluation results in Table 1. Even after we factor in the TCO of IoT-based CPS into the analysis above, we see the benefits still outweigh the cost in a huge margin with net cost savings amount to over 20 million NT dollars for an e-bicycle factory on a yearly basis. Overall benefits can be much larger if we take into account other quantifiable and non-quantifiable benefits not discussed in this experiment, such as lower human error, lower inventory, higher manufacturing efficiency, and higher PL visibility. For example, the number of improvements regarding tracking accuracy and assembly accuracy is estimated by Tbike and shown in Table 1.

Table 1. Operational efficiency improvements by IoT-based CPS

Performance evaluation of production logistic - IoT-based CPS vs. barcode based system	Barcode based production logistic operation	IoT-based non-line-of-sight (NLOS) production logistic operation	Estimated improvements (per year)
Time required to perform production logistic tasks (PLT)	112792.63 (hr)	4669.8 (hr)	Time savings 108122.83 (hr) (96 % decrease)
Labor cost to perform production logistic tasks (PLT)	NT$ 22558526	NT$ 702666	Labor cost savings NT$ 21855860 (97 % decrease)
Net cost savings			NT$ 21141860 (94 % decrease) (21855860 – 714000*) *Annual total cost of ownership (TCO) for IoT-based CPS
Tracking accuracy (bike frame) *(Estimated by Tbike)	Susceptible to misreads, losts, and human errors	Real time, NLOS tracking; 100% WIP visibility and data accuracy	98% reduction of frame tracking error
Assembly accuracy (critical parts) *(Estimated by Tbike)	Susceptible to assemble wrong parts to bike	Real time part validation for assembly tasks	99 % reduction of part assembly error

5.2 Experimental evaluation of the adaptiveness of CPS under dynamic environment

In a mass customization PL environment, manufacturing supply chain management plays a vital role in transferring critical parts to the production line at the right time with the right quantity. However, the dynamic changes of the production environment and the uncertainties from customer demand make it difficult to manage an optimal part inventory level to solve over stock or under stock problems. In this section, we will evaluate whether the proposed IoT-based CPS can improve the above issue using adaptive inventory control algorithms with real-time IoT information. Using the same emulation platform, the experimental in this section extends from a single company production scenario to a multi-firm supply chain coordination scenario.

To construct an IoT-based CPS in the context of multi-firm supply chain coordination, we must integrate the CPS with IoT-based manufacturing supply chain network based on the EPCglobal network infrastructure as suggested in Part 1 (referred to the preceding issue of IMDS). A multilayer modeling approach for an IoT-based based system was proposed in Part 1, and we applied that modeling scheme to design IoT-aware ontology model concept model, IoT-aware process model, and the IoT-aware object model (IoTOM). The IoTOM is shown in Figure 7 and depicts the cyberspace model of our IoT-based CPS testbed consisting of two participants (a manufacturer and a supplier) in the manufacturing supply chain network. Three iNodes were developed and deployed in the testbed to emulate the physical world system for suppliers' battery production and manufacturer's line-side buffer control and battery assembly stations. Specifically, we developed our IoT-based CPS on top of an IoT-based supply chain network to build a complete picture of an IoT-based PL and supply chain system. The physical machines of iNodes can communicate with each other using virtual tokens. We devise two types of virtual tokens for this study-parts token for battery and virtual kanban token. Figure 7 also shows that kanban tokens are moved with part tokens. This IoTOM is stored in IoT cloud, and its information is assumed to be shared to all supply chain participates in this case.

To evaluate the performance of our proposed IoT-based CPS in managing part inventory, we conduct an experiment on the testbed to investigate whether our proposed CPS with M2M distributed intelligence in iNode using adaptive inventory control algorithm can outperform current practice of Tbike using static inventory control logic under dynamic shop floor environment. For mass customization and hybrid production model, environmental changes of shop floor may result from the breakdown of machines, shortage of components, product rework, fluctuation of assembly time for different product models and configurations, and many other unforeseen disruptive events. We use parts inventory level at the line-side buffer station as the performance index to examine the difference between the static and M2M adaptive control models. The part chosen for our evaluation is battery since it is a critical component for e-bicycle. Since Tbike adopts JIT production strategy, the goal of the part inventory control is thus to minimize part safety stock while to have the required amount of parts arrive at the assembly station at the exact time when parts are needed. We first describe the emulation scenario behind the experiment and then discuss the experimental process and its results.

Based on the layout of the testbed in Figure 3, the intelligent buffer station emulates the line-side part inventory buffer of Tbike's facility. The iNode one on the right emulates the supplier's battery factory and the iNode two on the left emulate battery assembly station of Tbike. The three iNodes deployed at the testbed can communicate with each other with their wireless module and coordinate to accomplish tasks. Assembly workstation iNode uses Kanban token signals to pull battery parts from the intelligent buffer station. Then, the iNode at buffer station will request the part supplier to supply parts to Tbike based on Tbike's inventory control policy. To emulate the above-mentioned manufacturing supply chain with IoT-based CPS, we designed an inventory control scheme using RFID-based kanban approach. RFID-based kanban systems have been proven to be successful in improving inventory management (Bendavid *et al.,* 2010; Zhang *et al.,* 2005). The emulation scenario and its corresponding IoTOM are described in Figure 7. At the lower part of Figure 7 is a physical world system which shows the kanban-based PL control scheme for RFID tagged battery parts. On top of the physical system is cyberspace characterized by a colored Petri net (CPN) based IoTOM representing a close-loop adaptive supply chain network. The tag encoding scheme for battery part is also described at the bottom of Figure 7. The RFID tags are considered as replenishment kanban cards, which are reusable and circulated between the manufacturer and supplier. In our emulation system, each physical Kanban (a RFID tag) has its virtual counterpart, a corresponding virtual kanban token moving around in the IoTOM, as depicted in the lower part of Figure 7. As stated in Part 1, the IoTOM is shared among supply chain participants and distributed stored in the iNodes and IoT cloud. Each iNode manages part of the IoT-aware processes and thus stores part of IoTOM while the complete IotTOM and the model's emulation data are stored in the IoT cloud. Finally, the testbed implementation of RFID-based kanban system is illustrated in Figure 8, where the iNode M2M coordination mechanism using electronic (virtual) kanban token is explained. We used the virtual kanban token to replace purchase order token for handling part inventory replenishment, making these kanban tokens as message tokens to facilitate M2M communication of the testbed platform.

5.2.1 Experimental design

Based on the emulation scenario described in Figure 7 and the experiment objectives discussed above, the experiment setting is detailed in Table 2. The maximum capacity for the Lego buffer station is only three inventory slots. In this experiment, the Lego bicycle assembly station is configured to pull battery parts from the Lego buffer station. The battery assembly task is set to different processing rate in each time epoch to reflect the unpredictability and dynamic nature of manufacturing shop floor, as illustrated in Table 2. On the other hand, the speed of battery production is configured to a constant rate. The major performance indicator is the average buffer inventory, which is the mean value of buffer stocks per time epoch. Two buffer inventory control strategies are separately tested using the same experiment scenarios and testbed.

Strategy 1 (Static): It adopts a static or fixed inventory control model to manage battery inventory level.

Strategy 2 (Adaptive): It adopts an adaptive inventory control model to manage battery inventory level. This adaptive strategy is a real-time and context-aware inventory replenishment control model.

In our case study, the demand pattern of a certain class of bicycle battery part cannot be easily determined in advance under a hybrid and mass customization production model because each product is customized and the customer can choose from a variant of component options, making demand pattern for each part highly volatile. As intermittent nature of parts makes it a difficult task to calculate a consistent reorder point accurately, a base stock policy can be used to manage parts inventory with intermittent demand pattern (Scala *et al.,*, 2014). The base stock policy is equivalent to a continuous review (s, S) policy, with s = S−1, where "s" is the re-order point and "S" is the target inventory (Scala *et al.,* 2014).

In our testbed, the maximum buffer capacity is 3. Thus we assign three inventory policy plans based on three different target inventory level for this experiment: A (2, 3), B (1, 2) and C (0, 1). The three inventory policies are implemented as three executable inventory policy plans and stored in the knowledge base of buffer iNode. An executable plan denotes a controlling logic of an iNode in this study. Strategy 1 emulates a static pull strategy which is the current practice of many firms. Strategy 1 is set to execute Plan A at all times. Usually, a static inventory policy will cover a certain period before the policy change. On the other hand, the adaptive model of Strategy 2 will change inventory policy in real time through a context-aware IoT-based CPS. Thus, Strategy 2 will dynamically choose among the three executable inventory policy plans. The initial replenishment strategy of Strategy 2 follows that of Strategy 1 by executing Plan A. As the iNode detects changes in environment, it adjusts its goal to decrease or increase inventory level by executing plans A, B, or C. The adaptive inventory control algorithm and enforcing rules for the line-side buffer iNode are explicated in Tables 3 and 4. The enforcing rules have execution priority over inventory control algorithms. These algorithms and enforcing rules represent buffer iNode's reasoning. Thus they are implemented as decision rules and stored in iNode's reasoning module. Based on the above adaptive replenishment logic, the buffer station iNode at Tbike must coordinate with supplier's iNode to schedule battery parts deliverance as illustrated in Figures 7 and 8.

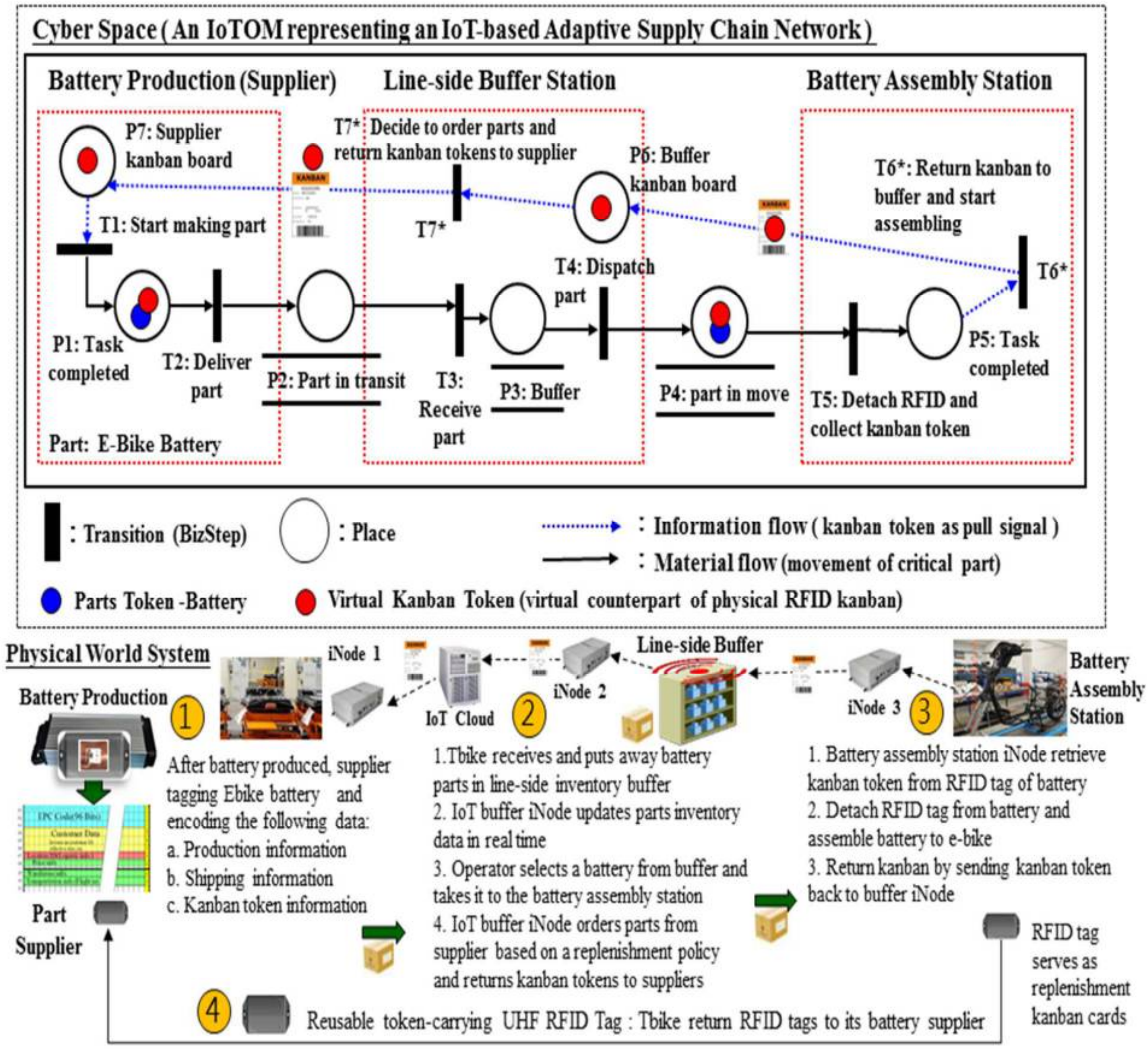

Figure 7. The emulation scenario: an inventory control scheme using an IoT and CPS based kanban control scheme

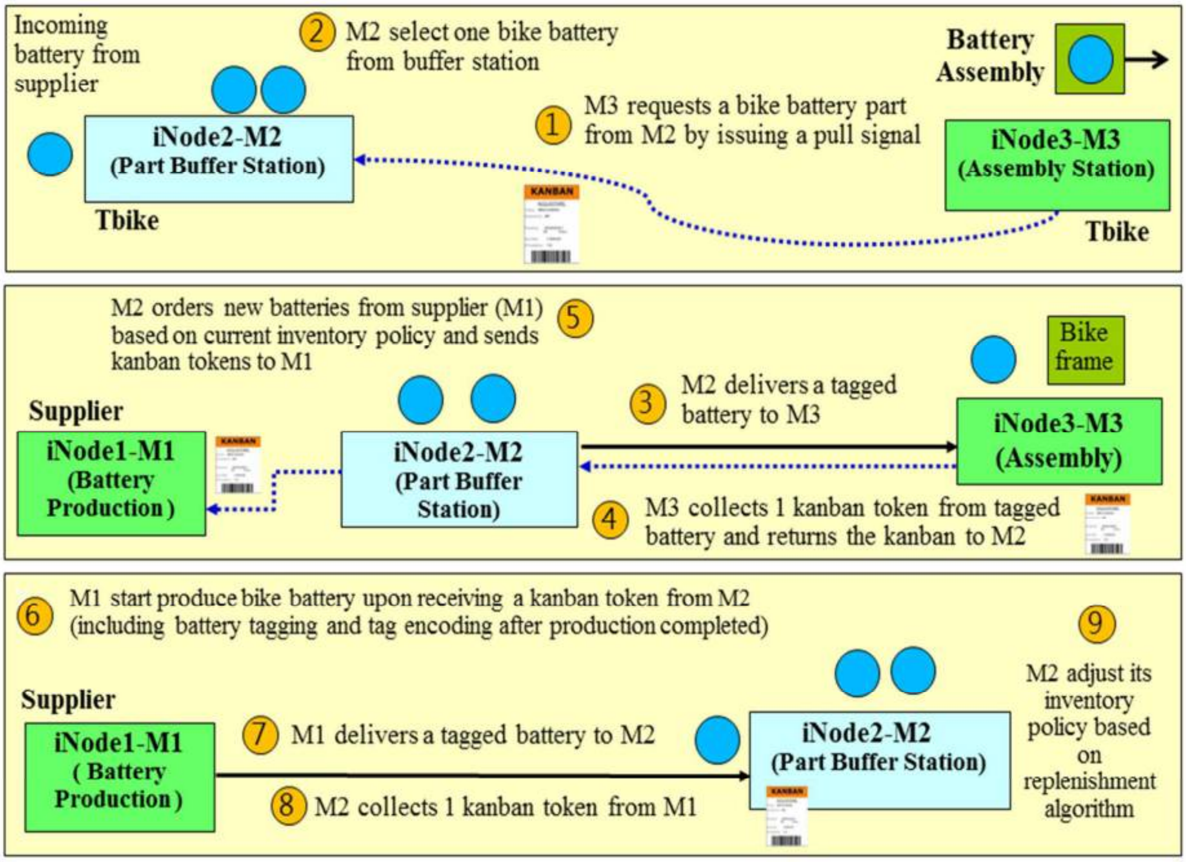

Figure 8. Testbed implementation for M2M coordination based on the proposed IoT kanban-based PL control scheme

Table 2 Adaptive inventory buffer control experiment setting

IoT-based CPS - Adaptive Inventory Control Emulation Experiment Setup

(1) iNode 1-Supplier's battery production workstation (N1): frame painting time is set to 2 minutes for all types of model
(2) iNode 2-Tbike's Line-side battery buffer station (N2): Inbound logistics time for battery part is set to 1 minutes
(3) iNode 3-Tbike's battery assembly workstation (N3): Tbike adopt hybrid production so that each e-bike is custom made with different configurations. In this case, the battery assembly time may vary among different models and thus the variation is set between 4~8 min
(4) Conveyer 1 moving time is set to 0.2 min
(5) Conveyer 2 moving time is set to 0.2 min
(6) Inventory Policy [s, S] : A (2,3); B (1,2); C (0,1) ; * In the (s,S) policy, s represents reorder point and S is the target inventory
(7) Time Epoch: Time between two pull requests from N3

Experiment Scenario

Time Epoch	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15
Variation pattern of electric bike assembly time (min)	4	5	5	4	7	6	6	8	6	5	6	4	6	5	5

Table 3. An adaptive inventory control algorithm adopted by the buffer station

```
IF | The percentage change in AvgInv | < 10%
THEN
MAINTAIN Current Goal ( keep current inventory_policy_plan[R] )
END IF

IF ( The percentage change in AvgInv > 10%) AND (Current AvgInv > = 1 )
THEN
UPDATE Agent's Goal ( New Goal = Decrease Inventory Level )
Adopt New Inventory Policy ( drop current plan and select new inventory_policy_plan[R-1] )
ELSE IF ( The percentage change in AvgInv > 10%) AND (Current AvgInv < 1 )
THEN
UPDATE Agent's Goal ( New Goal = Increase Inventory Level )
Adopt New Inventory Policy ( drop current plan and select new inventory_policy_plan[R+1] )
END IF

IF ( The percentage change in AvgInv < -10% ) AND (Current AvgInv > 1 )
THEN
UPDATE Agent's Goal (New Goal = Decrease Inventory Level)
Adopt New Inventory Policy ( drop current plan and select new inventory_policy_plan[R-1] )
ELSE IF ( The percentage change in AvgInv < -10% ) AND (Current AvgInv <= 1 )
THEN
UPDATE Agent's Goal (New Goal = Increase Inventory Level)
Adopt New Inventory Policy ( drop current plan and select new inventory_policy_plan[R+1] )
END IF

*R : the reorder point of current inventory policy
```

Table 4. Enforcing rules adopted by the buffer station

```
# Enforcing Rule 1.
IF (Current AvgInv < 1 ) AND (Previous AvgInv < 1 )
THEN
UPDATE Agent's Goal (New Goal = Increase Inventory Level)
AdoptNew Inventory Policy ( drop current plan and select new inventory_policy_plan[R+1] )
END IF

# Enforcing Rule 2.
IF ( Inventory level is decreased to 0 )
THEN
 REQUEST part(battery) from Supplier(battery)
END IF
```

5.2.2 Experimental results

Experimental results are shown in Figures 9 – 12. Figure 9 shows the buffer inventory change over experimental time using static inventory control scheme and Figure 10 displays the buffer inventory change over experimental time using M2M CPS based adaptive inventory control scheme. The adaptive control scheme outperformed static control scheme as the inventory level in Figure 10 is lower for most of the time compared to that of Figure 9.

Figure 11 also shows the adaptive control scheme clearly outperformed static one regarding average buffer inventory. Finally, Figure 12 shows that adopting the adaptive control scheme not only considerably reduce battery inventory for Tbike but also having Tbike's supplier produce less battery during the experiment period. The results shown in Figure 12 indicate that using IoT technology and M2M distributed intelligence; the IoT-based CPS can construct a virtual lean supply chain network to decrease overall inventory level across the entire supply chain.

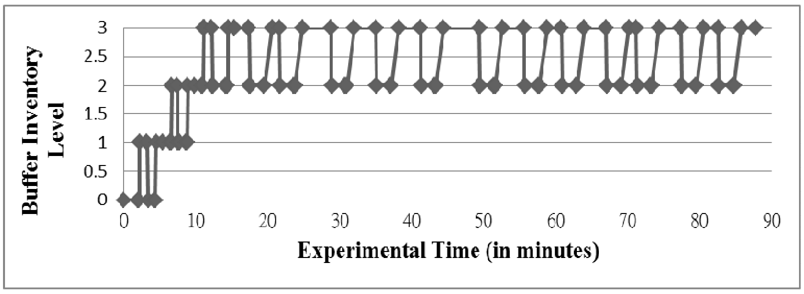

Figure 9. Inventory change over time-base case using static inventory control policy

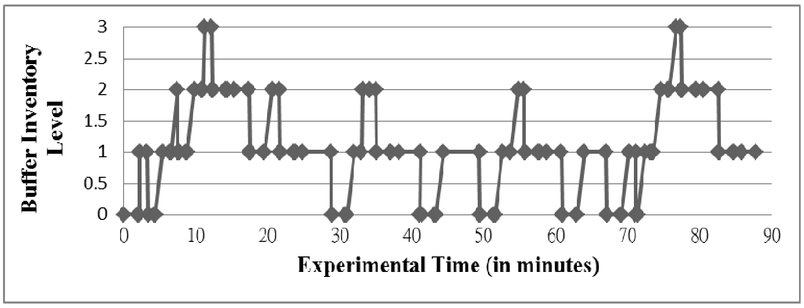

Figure 10. Inventory change over time-M2M CPS-based adaptive control scheme

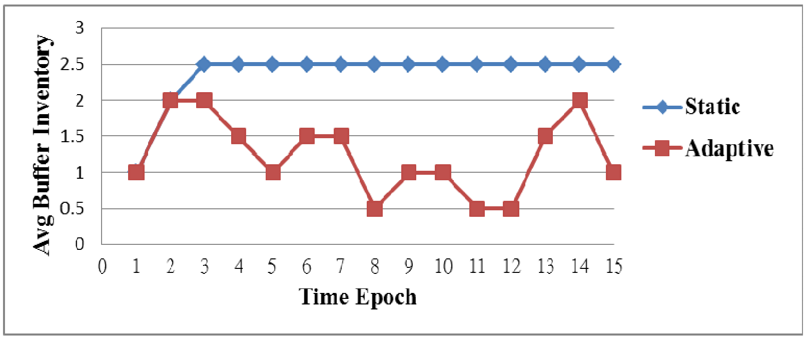

Figure 11. Comparison of two inventory control models

A statistical test is used to verify whether there are significant differences in performances between adaptive and static strategies using data sets from Table 5. The result of paired t-test shows the p-value is significantly lower than the critical α value of 0.05 for a two tail test. The statistical result indicates that there is a significant difference between the two control schemes regarding average buffer inventory.

Table 5. Data results for test runs under two competing models

Time Epoch	μ_1 (Static)	μ_2 (Adaptive)	Difference $d =$	d^2
1	1	1	0	0.00
2	2	2	0	0.00
3	2.5	2	0.5	0.71
4	2.5	1.5	1	1.00
5	2.5	1	1.5	1.22
6	2.5	1.5	1	1.00
7	2.5	1.5	1	1.00
8	2.5	0.5	2	1.41
9	2.5	1	1.5	1.22
10	2.5	1	1.5	1.22
11	2.5	0.5	2	1.41
12	2.5	0.5	2	1.41
13	2.5	1.5	1	1.00
14	2.5	2	0.5	0.71
15	2.5	1	1.5	1.22
	(Avg) 2.37	(Avg) 1.23	(Σ) 17	(Σ) 14.56

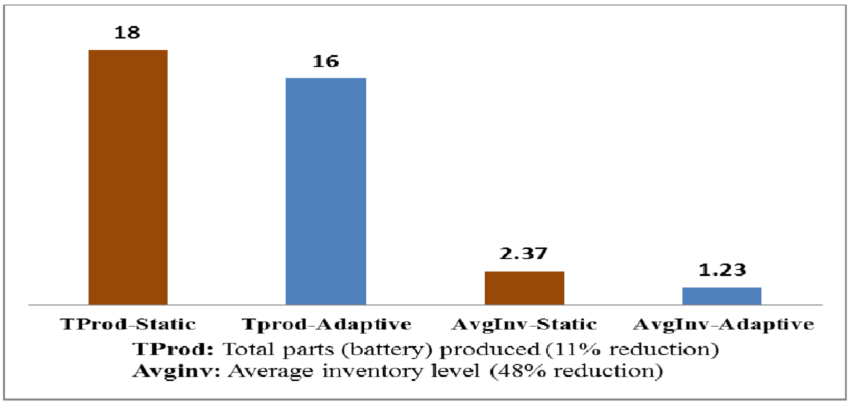

Figure 12. Lean performance evaluation of the experiment

The experiment results entail important implications for both Tbike and its part suppliers in accessing the value of Industrial 4.0 using IoT-based CPS. This case study illustrates that using distributed machine intelligence of iNode on the shop floor creates a control loop that enable the IoT-based CPS to receive the real-time feedback from its environment and then adapt to the changing environment by adopting different inventory control policies to achieve the goal of lean supply chain management of battery parts without human intervention. The proposed IoT-based CPS also demonstrates that the ability to communicate with each other among IoT-enabled machines allows for an adaptive reaction to production changes of upstream and downstream processes. Furthermore, the results show that an adaptive CPS using distributed intelligence outperformed the non-adaptive one in managing parts inventory with intermittent demand pattern. By incorporating the adaptive intelligence in CPS, the experiment showed that Tbike had reduced its buffer inventory level, and the benefit also propagated to Tbike's upstream bike battery supplier by lowering the total parts produced while allowing the supplier to meet the Tbike's part demand in time. The above analysis reveals a salient capability of our proposed CPS framework. The context-awareness designed in our IoT-based CPS enables the intelligent machines (i.e. iNode) to sense upcoming changes in a production environment, such as the demand pattern changes of parts in this case, and take proactive actions to adapt to new changes, such as changing parts inventory control policies as illustrated in the experiment. The above experimental results also indicated the context-awareness feature of the IoT-based CPS could help achieve lean supply chain management for both Tbike and his battery part supplier.

6. Practical implications

Mass customization production increases the dynamics and complexity of shop floor operation and poses new challenges to manufacturing firms. However, current barcode tracking system alone is not sufficient for PL in an IoT-enabled smart factory. Using IoT technologies such as ultra-high frequency (UHF) RFID in the product or component tagging, the proposed IoT-based CPS can easily retrieve or store product pedigree information from or in RFID tagged products and their associated parts, enabling the CPS to detect counterfeit parts during assembly and identify anomalous events in real time. As discussed in Section 5.1 about operational efficiency for PL, RFID technology is an optimal alternative to the conventional barcode system, providing such strengths as increased data capacity and the ability to read and write tags without line of sight. IoT-based CPS thus can minimize human intervention in barcode tagging and data capturing and reduce the number of manufacturing errors and the chance of producing unsafe products. Based on the IoTOM described in Part 1 of this research and the architecture framework proposed in this article for IoT-based CPS as an implementation reference model, a manufacturing can develop IoT-based PL and supply chain applications to 1) connect different entities in a multi-echelon supply chain based on the IoTOM's structure, 2) coordinate the activities of a supply chain through information sharing and M2M coordination mechanisms embedded in the CPS's control logic, and 3) share the same supply chain network model and model's state to all parties in the same manufacturing supply chain. In other words, a manufacturing enterprise and its key supply chain partners can collectively build a manufacturing supply chain network model using our proposed modeling scheme in part 1 and then develop and deploy CPS in their manufacturing sites based the design models (ex, IoTOM) and the proposed implementation architecture for IoT-based CPS. Several advantages of our proposed framework were also observed during system implementation. An architectural advantage of our design is the role iNdoe plays in the proposed framework. An iNode controlling device serves as an intelligent endpoint of the whole CPS, and it is decoupled with the IoT devices and machines in the shop floor and the IoT cloud. This decoupling design preserves the low-level control logic such as PLC (Programmable Logic Controller) codes in shop floor machines and separate them from the higher-level control logic of iNodes so that each iNode's control logic and be easily replaced and modified without affecting operation logic in machines or devices. This design allows for easy reconfiguration of CPS, which is a very import trait in a flexible and reconfigurable manufacturing environment.

As shown in the experimental studies of Section 5, the IoT-based CPS demonstrated its capability to enable non-line-of-sight PL operations, provide full visibility of production process in real time, and minimize operation errors (with iNode's HMI) in the first evaluation regarding operational efficiency for PL tasks. On the other hand, we designed and conducted an experiment on the testbed for the second evaluation to show the salient characteristics of intelligence, connectedness, and responsiveness implanted in our developed CPS. We found that as production and logistics information are shared among all IoT-based CPSs owned by different supply chain participants, operations among supply chain activities of different partners can be synchronized, and the entire supply chain can become more adaptive to changing the environment and optimized the inventory management. These capabilities allow companies to perform dynamic operation process control and ensure the successful execution of lean production strategy.

The findings obtained from the evaluation and experimental results of the IoT-based CPS prototype shown that our proposed framework can be applied in the industrial management of PL beyond the boundary of the single production site to include supply chain partners supplying critical parts. The testbed platform built upon the case study emulated the application scenario of a discrete manufacturing factory. The case study also showed that the proposed architecture framework and prototype system can be applied to many discrete manufacturing industries, such as automobile, airplane, bicycle, home appliance, and electronics. An important implication from the experiment of this article is the envisioning of a future automated intelligent manufacturing supply chain network. With the RFID and CPS based kanban control scheme implemented in IoT-based CPS and installed in each business entity alone a networked supply chain, the procurement process between buyer (manufacturer / retailer) and seller (part suppliers / product manufacturer) can be fully automated and dynamically adjusted based on market changes so that inventory level and inventory cost of the entire supply chain are minimized.

7. Conclusion

This article proposed an IoT-based CPS architecture framework to realize cyber-physical integration and real-time adaptive PL control. Laboratory scale prototype system and testbed were developed to illustrate PL applications and experiment with the key aspects of the IoT-based CPS in application scenarios. The emulation testbed developed in this study can serve both research and education purposes. The use of Lego system to emulate real robots and workstation greatly lower the cost of building an IoT-based CPS prototype for PL without losing educational value, especially for budget constrained laboratories. Based on the case study of this article and its application scenarios, the emulations and experiments were conducted on testbeds to evaluate the proposed IoT-based CPS. Results showed that the IoT-based CPS could cost-effectively perform NLOSPL tasks, align physical material flow and information flow, reduce part inventory, and adapt to environmental changes. These results also imply that adopting IoT-based CPS can significantly improve PL operation in a dynamic shop-floor environment. As shown in the experimental results, the context-awareness of our proposed IoT-based CPS can help an enterprise transform to a more flexible and efficient organization to succeed in a highly dynamic and competitive environment. However, there are still many challenges concerning the practicability of adopting these new technologies in a realistic manufacturing and logistics environments, such as the effort to integrate IoT-based CPS with diverse IoT devices and enterprise systems (ex. ERP, MES), and the lack of a standard for M2M communication protocol across supply chain participants. This research opened up new research directions toward IoT-based CPS in PL and supply chain applications, and also provided a practical guideline for the future development of IoT-based CPS.

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