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Intelligent assembly system for mechanical products and key technology based on internet of things

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Abstract The Internet of Things (IoT) has a significant effect on the development of manufacturing technology. Therefore, according to the analysis of the challenges and opportunities faced by manufacturing industry, this study uses the assembly process of mechanical products as the research object and analyzes the characteristics of IoT-based manufacturing systems. To improve the interconnection, perception, efficiency, and intelligence of the assembly system, this study proposes the concept of IoT-enabled intelligent assembly system for mechanical products (IIASMP). The IIASMP framework, which is based on advanced techniques such as information and communication technology, sensor network, and radio-frequency identification, is then presented. Key technologies under this framework, including assembly resources identification, information interaction technology, multi-source data perception and fusion, intelligent assembly agent, and value-added data and dynamic self-adaptive optimization, are described. Finally, the current results of IIASMP are described in the case study. The proposed framework and methods aims to have an important reference value for applying the key technologies and be used widely in the intelligent manufacturing field.

Keywords Intelligent assembly system · Internet of things · Dynamic self-adaptive optimization · Information interaction technology · Intelligent assembly agent

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Introduction

Global competition in the manufacturing field is becoming fierce, and manufacturing systems are unable to cope with the requirements of mass customization (Michalos et al. 2010). Therefore, the manufacturing industry must achieve the main objective (i.e., to produce high-quality products at the lowest possible cost) to cope with the said requirements. With sharply increasing costs and competition, the growing complexity of achieving this objective has forced manufacturing enterprises to look for alternatives to the traditional approaches of design, manufacturing, and management (Nasr and Kamrani 2008). The rapid development of advanced technologies has led to the rapid evolution of intelligent manufacturing systems (IMSs) and the improvement of IMS characteristics (Nasr and Kamrani 2008; Oztemel 2010) such as adaptation, autonomy, self-progress, learning, and automated maintenance. New technology-enabled systems are being developed with short time frames. IMS is becoming increasingly dominant in industrial and manufacturing areas, and the changes of IMS surprises both the academic and industrial community (Oztemel 2010).

Many governments and organizations have recognized the trend of deploying the Internet of Things (IoT) and related services in the manufacturing industry to achieve intelligent manufacturing (IM), promote the intelligence of the production system, and achieve the main objectives. Germany proposed the Industry 4.0 strategy, which presents that the IoT and related services enable the creation of networks that incorporate the entire manufacturing processes that convert factories into smart environments. The United States, Japan, South Korea, and some European and Asian countries have formulated their own IoT strategies and market positions. Many companies are trying to develop and apply IoT technology with the encouragement of the Chinese government to enhance the intelligence of the production system. Therefore, IoT technology has a significant effect on the development of manufacturing technology. Some advanced technologies (e.g., information and communication technology (ICT), sensor network, and radio-frequency identification (RFID)) have been rapidly developed over the last decade, thus nurturing the emergence of the IoT. IoT technology aims to capture and monitor real-time object information to achieve smart perception, recognition, optimization, and management in enterprises, factory, shop floors, etc. IoT technology has comprehensive sense, reliable delivery, and intelligent processing features. IoT technology are now used in the industry manufacturing field, but a complete IMS based on IoT and other advanced manufacturing technologies still need some time to be formed. Thus, manufacturing systems will become increasingly intelligent with the development of IoT technology. “Smart” has been considered as a core characteristic of the future manufacturing system. Therefore, issues related to the process of representing, interconnecting, integrating, and organizing the information generated by IoT will become popular.

Currently, technologies such as different types of barcodes, active and passive RFIDs, and sensor networks play important roles in promoting IoT. Atzori et al. (2010) presented that IoT is a novel paradigm with three visions: things-oriented vision, Internet-oriented vision, and semantic-oriented vision. IoT needs identification technology, sensing technology, communication technology, and middleware technology as key enabling technologies. Identification and sensing technology are involved in things-oriented vision, communication technology is used for Internet-oriented vision, and middleware technology is for semantic-oriented vision. The functionalities offered by IoT-enabled smart items can be grouped into five abstract categories, including information storage, information collection, communication, information processing, and performing actions (Chaves and Nochta 2011). The production system consists of marketing, design, scheduling, and manufacturing processes (Oztemel 2010). The manufacturing processes are composed of several stages, including resources identification, resources recognition, data collection, data transmission, data mining, and feedback control. The manufacturing system can better achieve the production objectives only through these stages. Assembly processes are important steps in product manufacturing and directly affect the quality of products. Therefore, on the basis of analyzing the manufacturing processes stages and IoT visions, IoT has the following specific contextual meaning in the current research: resource identification, sensing, communication and interaction, data fusion and integration (middleware), and IoT-based applications.

The competitive market environment and advanced technologies accelerates the development of IM. Some progressive technologies (e.g., RFID and sensors) have been widely used in manufacturing systems. Although enterprises have been enriched with new technologies for high flexibility potential, the following research questions still exist:

1. How should manufacturing resources be encoded to support the data parsing, exchange, processing, and sharing under an IoT environment?
2. How should the massive data captured by IoT-enabled heterogeneous devices be transferred and integrated?
3. What methodology should be used for value-added information to support the decision-making process of the enterprise?
4. How to achieve optimization for manufacturing processes based on real-time information perception?

The research object of this paper is the assembly processes of mechanical products. To address the above research issues, an IoT-enabled smart assembly system for mechanical products is proposed on the basis of the analysis of IMS and IoT feature characteristics. These IoT-enabled assembly systems are composed of smart machines, storage systems, and production facilities, which are capable of exchanging information autonomously while triggering actions and controlling each other independently.

In the IoT-enabled intelligent assembly environment, the concept, infrastructure, and key technologies of IoT-enabled intelligent assembly system for mechanical products (IIASMP) are proposed on the basis of the analysis of manufacturing process stages, IoT visions, IoT features, and IMS characteristics. The presented IIASMP framework integrates some key technologies (e.g., information perception, transmission, and extraction) to implement the decision optimization of assembly processes and intelligent operations of the assembly system. These key technologies are for the steps of different processes.

The remainder of this paper is organized as follows. The definition and characteristics of IIASMP are presented after reviewing the literature. On the basis of these concepts, the framework and key technologies for IIASMP are presented in detail. Thereafter, the relationships between IIASMP and other enterprise systems are shown. The limitations, problems, and expected benefits of the proposed approaches are expressed. A case of study is then discussed to demonstrate the current research on IIASMP. In the last section, conclusions are drawn and the challenges and future works of IIASMP are discussed.

Literature review

The following literature categories are relevant to this research.

Resource catalog, coding, identification, and information collection techniques

Manufacturing resources play an important role in production systems and information interaction. Therefore, a basic standardization resource catalog and coding can simplify information parsing, exchange, processing, integration, and sharing. Zhang et al. (2006) presented an effective coding approach for multi-objective integrated-resource selection and operation sequence problems in IMS. Jiang et al. (2006) constructed the hierarchical structure of the ontology information coding system by analyzing the relationship between sub-domains and information objects.

Various resource-encoding schemes are used to accommodate the data captured by data collection devices. The rapid development of advanced techniques has led to the abundance of various types of identification technology (e.g., barcodes, RFID, and sensors) for manufacturing systems. Youssef and Salem (2007) presented an effective method to use barcodes for positioning and recognition purposes. However, some enterprises still use barcode systems to manage manufacturing processes. These systems often require human intervention during the manufacturing process. Recently, sensors, images, and visual recognition technologies have been widely used for item identification. For example, Atlas et al. (1996) addressed the advantage of using sensors to monitor machine status and manufacturing processes. Edinbarough et al. (2005) presented a neural-network-based vision-inspection system interfaced with a robot to detect and report IC lead defects online. Golnabi and Asadpour (2007) discussed the design methodology of industrial machine-vision systems and reported a generic machine-vision model. RFID is also being widely used to manage and control manufacturing systems, such as real-time production management systems for motorcycle assembly lines (Liu et al. 2012), manufacturing information tracking infrastructure (Zhang et al. 2012), manufacturing execution system (Dai et al. 2012), and shop-floor material management. These approaches contribute to the revitalization of RFID efforts in manufacturing industries by presenting a real-life case study that involves the use of RFID for managing material distribution in a complex assembly shop floor at a large air conditioner manufacturer (Qu et al. 2012). Zhang et al. (2012) proposed the IM resources with the combination of traditional resources, RFID, barcodes, and sensor techniques.

Information communication and interaction techniques in enterprises

The Internet is a milestone for information and communication technologies. Research on the Internet started in the early 1960s, advanced in 1973, and was popularized in the 1990s. In recent decades, various types of information interactions and communication techniques [e.g., bluetooth, infrared, ZigBee, bus, sensor network, and electronic product code (EPC) network] are available for manufacturing systems with the rapid industrialization and informatization for enterprises. Some relevant cases have been illustrated. The infrared imager is used to monitor the health of a few manufacturing processes (Al-Habaibeh and Parkin 2003). Aguilar-Ponce et al. (2007) presented a type of sensor network architecture for sensor-based scene surveillance for detection and tracking objects of interest through the application of agents. Profibus networks are used in real-time systems with flexible scheduling (Silvestre and Sempere 2007). The lean enterprise service bus architecture is proposed to enhance the interoperability between the production system and global enterprise information system in terms of business and manufacturing requirements and establishes semantic interoperability for industrial semantics (Zayati et al. 2012). As early as 1999, the Auto-ID center practically drove the rapid and escalating diffusion of the EPC. Cutting-Decelle et al. (2007) proposed a way of managing modularity in production management systems by using standardized information models. Drath et al. (2008) indicated that the basic architecture of the neutral data format automation markup language (AutomationML). AutomationML is a neutral data format based on XML for the storage and exchange of plant engineering information. AutomationML is provided as an open standard. The goal of AutomationML is to interconnect the heterogeneous tool landscape of modern engineering tools in different disciplines, e.g., mechanical plant engineering, electrical design, HMI development, programmable logic controller (PLC), and robot control. Thiesse et al. (2009) also discussed the technology, standards, and deployments of the EPC network. An application of ZigBee combined with an embedded system for industrial real-time measurements represents innovative technology (Sung and Hsu 2011).

Optimization techniques for manufacturing system

The manufacturing environment today is uncertain and continually changing. Uncertainty is an inevitable consequence of the complexities that technological advancements and other factors generate (Jain et al. 2013). To survive in the fierce competition, manufacturing systems are required to have the ability to quickly adjust to any changes, such as product, processes, loads, and machine failures (Beach et al. 2000). Jain et al. (2013) concluded that process uncertainty factors include machine, material and handling devices, work in progress (WIP), buffer, multi-skilled workers, and redundant equipment. Therefore, maintaining the stability of manufacturing systems becomes the most important problem for enterprises. Optimization research for manufacturing processes is conducted because of this problem. Some relevant techniques have been proposed and widely used in manufacturing systems. Kumar et al. (2000) discussed a quality optimization methodology based on the Taguchi approach and the utility concept. Deshpande and Cagan (2004) introduced an agent-based optimization algorithm that combines stochastic optimization techniques with knowledge-based search. The differential evolution for sequencing and scheduling optimization can be seen in the study of Nearchou and Omirou (2006). The resource optimization deployment is modeled as a multi-objective optimization problem (Changfeng et al. 2006). Chiu (2008) was concerned with the optimization of production running time and considered the stochastic breakdown and reworking of defective items. The dynamic optimization driven by real-time perception data is considered a core characteristic of next-generation manufacturing systems (Zhang et al. 2012).

Agent-based manufacturing technology

Given that agent technology is an important aspect within artificial intelligence research, this technology is considered a significant approach for developing manufacturing systems. Agent-based technology has been employed to perform a number of tasks including, but not limited to, production planning, scheduling and execution control, enterprise integration and supply chain management, materials handling, and inventory management (Madejski 2007). Studies have disclosed various definitions and applications for agents. Luck and d'Inverno (2001) applied formal methods to provide a defined framework for agent systems. Guo and Zhang (2008) considered that the agent can possess basic attributes (e.g., object, knowledge, and label) composed of functional units, such as communication module, processing module, inference module, and study module. Ruiz et al. (2011) discussed an agent-supported simulation environment for IM and warehouse management systems. Sabar et al. (2012) proposed an approach for a multi-agent-based algorithm for personnel scheduling and rescheduling. This algorithm mainly considers individual competencies, mobility, and employee preference, as well as the competency requirements associated with each assembly activity with respect to both the current master assembly schedule and line balancing for each product. Agent-supported manufacturing systems have been further promoted with the use of RFID technology, such as RFID-enabled intelligent agent system (Trappey et al. 2009), agent-based distributed production-control framework with the UHF RFID technology (Tu et al. 2009), and agent-based workflow management for RFID-enabled real-time reconfigurable manufacturing (Zhang et al. 2010).

Internet of things

The basic idea of the IoT is that the pervasive presence around us is composed of a variety of things or objects, such as RFID tags, sensors, and actuators. These things or objects can interact with each other and cooperate with their neighbor resources to reach common goals through interaction standards (Giusto et al. 2010). IoT is a novel paradigm that have been widely used by researchers and practitioners to describe the combination of real-world physical objects and the virtual world of information technology (Atzori et al. 2010). However, the term "Internet of Things" is a fuzziness term. The reason of the apparent fuzziness around this term is a consequence of the name "Internet of Things," which is syntactically composed of two terms. The first word pushes toward a network-oriented vision of IoT, whereas the second word focuses on generic "objects" that will be integrated into a common framework (Atzori et al. 2010). The vision of IoT is still a broad vision. Atzori et al. (2010) presented that the IoT paradigm will be the result of the convergence of three main visions, including things-oriented vision, Internet-oriented vision, and semantic-oriented vision.

The combination of the words "Internet" and "Things" assume a meaning that introduces a disruptive level of innovation into the ICT world. Although IoT is a popular issue, this detail is not forgotten. IoT semantically means "a world-wide network of interconnected objects that are uniquely addressable on the basis of standard communication protocols" (Atzori et al. 2010). For ICT technology in manufacturing, Chryssolouris et al. (2009) described the evolution of information technology systems in manufacturing (e.g., computer-aided technologies, manufacturing control, simulation, resource planning, and optimization), outlined their characteristics, and presented the challenges to be addressed in the future. Global competition in the manufacturing field is becoming increasingly fierce, and manufacturing systems are unable to cope with the requirements of mass customization; thus, manufacturing industries be enriched with new technologies for to achieve a high flexibility potential. Michalos et al. (2010) presented that technologies directly dealing with assembly processes, such as handling, joining, human resources, and supporting systems, are mainly information technologies. At the operating level, IT systems support different tasks, such as material and workflow planning, order control and monitoring, process optimization modeling, shop floor documentation, quality management, maintenance management, vehicle identification, and others (Michalos et al. 2010).

Intelligent manufacturing system

The manufacturing industry has gone through many changes, i.e., manual operation, mechanization, automatization, informatization, integration, and intelligence. Industrialization realizes the liberation of human manual labor, and informatization further realizes the liberation of human mental work. IM has been developed in recent years. IM is a man–machine integrated intelligent system composed of an intelligent machine and human experts, which can conduct smart activities, such as analysis, inference, judgment, conception, and decision-making during manufacturing processes (Guo and Zhang 2009). IMS can conduct analyses, judgment inferences, conceptualizations, and decisions regarding manufacturing problems. This system aims to replace or extend part of the human brainwork in the manufacturing environment and collect, store, improve, share, inherit, and develop the manufacturing intelligence of a human expert. The concepts of intelligent manufacturing technology and IMS have been proposed in the late 1980s and early 1990s with the development of artificial neural-network techniques. Since the proposal of IMS, this system has become one of the popular research points in the manufacturing domain. Artificial intelligence techniques have been used in IM for more than 25 years. As early as the 1993s, Monostori and Prohaszka (1993) described different approaches for applying artificial neural-network techniques for modeling and monitoring machining processes (e.g., turning and milling) with sensor integration. Zijm (2000) established a basic framework for IM planning and control systems. McFarlane et al. (2003) explored the manner in which both conventional control methods and distributed intelligent control methods can be enhanced by the availability of accurate and timely information about an item. Bargelis et al. (2004) developed the knowledge-based framework of an intelligent functional model. Oztemel and Tekez (2009) introduced a reference model for intelligent IMS. Jardim-Goncalves et al. (2011) presented a knowledge framework to address this challenge and made interoperable IMSs a reality, which proposes the use of semantically enriched international product data standards and knowledge representation elements as a basis for achieving seamless enterprise interoperability. Makris et al. (2012) discussed an integration-driven framework for enabling the RFID-based identification of parts to perform robotic assembly operations in a random mix. The objective of this research is to enable robotic cell control logic and to identify the component variants that need to be welded, namely, the part dimensions and the type of material. On the basis of the identification processes, the robots should run the appropriate program to perform the handling and joining processes. The rapid development of advanced technologies will increase the popularity of research on IoT-enabled IMS in the manufacturing domain.

Definition and characteristics of IIASMP

Manufacturing systems has to meet the following requirements to achieve their main objectives: interoperability, fault tolerance, cooperation, scalability, information integration, distributed organization, heterogeneous environments, open and dynamic structure, agility, and human–software–hardware integration (Madejski 2007). On the basis of IMS characteristic analysis (Madejski 2007; Nasr and Kamrani 2008; Oztemel 2010) and IoT features (e.g., comprehensive sense, reliable delivery, intelligent processing features, and so on), an IIASMP is proposed. The present research considers that an intelligent assembly system for mechanical products consists of smart equipment, an ubiquitous sensor network, and an expert system. Assembly resources (material, equipment, personnel, energy, and environment) and their statuses in this intelligent system can be collected, analyzed, and extracted on the basis of resource identification technology, multi-source multi-sensor information fusion technology, man–machine interaction technology, intelligent assembly agent technology, and self-adaptive optimization technology to achieve the decision optimization of the assembly processes and the intelligent operation of the assembly system. The IIASMP characteristics in an IoT-enabled intelligent assembly environment are as follows:

1. Multi-source multi-sensor information fusion. This characteristic denotes that assembly resources (e.g., material, equipment, personnel, energy, and environment) and their statuses can be sensed, extracted, and integrated. Advanced technologies have increased the transparency of manufacturing processes. Multi-resources are usually equipped with multi-sensor components, which have perceived capabilities. For example, measuring machines are always attached to functional sensors (e.g., torque sensor, angle sensor, temperature sensor, pressure sensor, and vision sensor) to perceive the quality parameters of products. Materials, products, and workers are usually equipped with RFID tags, barcodes, and IC cards, which can be sensed by data terminals (RFID readers, scanning guns, and IC machines). All collected data are transmitted and fused at the end of the process.
2. Self-regulation and self-organization. This characteristic means that this system can collect and understand its own status information and analyze and regulate its own behavior. For instance, a material-handling robot is composed of a machine vision, a smart controller (e.g., PLC and graphic workstation), an actuator (e.g., robot arm and servomotors), and a knowledge base (e.g., standard image database, image processing algorithm, and encoding rules). Machine vision is applied to capture the images of materials, which are processed by graphics workstation to achieve materials recognition (materials type) and location (3D coordinates of materials) on the basis of a standard image database and algorithm. Therefore, the PLC can control the robot arm and servo motors on the basis of 3D coordinates to complete the active handling of materials and other related tasks without external human interference.

3. Self-adaptation. The system can tolerate and handle disturbances during the assembly process. For example, if the RFID tag can store the quality information of each workstation, the system can modify the tolerances of the current workstation on the basis of pre-workstation tolerance deviation because of the quality defect accumulation from each workstation. Thus, the system can adapt tolerance deviation, reject non-conforming products, and improve product quality. RFID tags usually are attached to pallets with products.
4. Self-learning. The system is capable of being trained to conduct certain tasks. Learning involves memorizing and correcting the interpretation of context-dependent meanings. For example, if the sample sizes of memorized tolerances deviation (pre-agent) and modified tolerances (current agent) are large, the sample data will be directly analyzed and can be used to change some related tolerance ranges stored in the system knowledge base.
5. Self-maintenance. The system is capable of maintaining its own state of operational readiness through self-diagnosis, preventive self-maintenance and, self-repairs via reconfiguration. For example, a machine can identify a faulty component and undergo reconfiguration to replace the faulty part with a stand-by component capable of self-maintenance.
6. Man–machine integration. The system can integrate machine and human intelligences and can cooperate with the other. For example, machine vision provides a powerful tool for the interaction between man and machine. Machine vision can recognize human gestures, and each gesture presents an actual command that will force a machine to perform specific actions, such as device resetting, device boot, and device shutdown.

Overall framework of IIASMP

The purpose of this research is to apply IoT technology and develop an IIASMP. Figure 1 shows the overall IIASMP framework. This infrastructure mainly involves five main layers and one system service part. The bottom layer is a sensing assembly and net layer. The other layers include the information integration layer, decision making and application layer, and interface layer. The last layer is the knowledge representation (high-level systems) layer, which has been researched and used for a long time. Each layer will be described in the following:

1. Sensing assembly layer. In the sensing assembly layer, assembly resource identification technology and multi-source and multi-sensor data acquisition technology are adopted to sense and collect the status data of assembly resources. Thereafter, these resources adjust their status or perform some action according to the feedback instructions from the decision making and application layer to complete the assembly processes.
2. Net layer. The net layer consists of a field bus, a sensor network, the Internet, an industrial Ethernet, a network management system, and a data management system. In this layer, the sensing data can be protocol converted, stored, routed, and transferred.
3. Sensor data fusion layer. In the sensor data-fusion layer, the sensing data from the middleware can map all the statuses and behavior of assembly resources. Thus, data becomes information, which can be extracted and integrated.
4. Decision making and application layer. In the decision making and application layer, the integrated information from the last layer can be monitored, analyzed, and extracted. Thereafter, the integrated information can support the intelligent management control of the system by using man–machine interaction technology.
5. System service part. The system service part is involves all four layers. This part provides resource configuration, data security, protocol conversion, and other related services.
6. Interface layer. Interfaces are the communication devices that different systems use for exchanging data. In this study, interface technologies, such as web services, files, sockets, messages, relational databases, or other technologies, support the duplex transmission of data. The interface of other systems will be introduced in a later section.

On the basis of discussing the functions of the layers, this study will discuss how the proposed system “pairs” or works with existing technologies. Manufacturing systems consist of many heterogeneous resources (e.g., sensors, PLC, data collection, and communication terminal) by using different communication protocols and standards to achieve comprehensive sense, sharing, and cooperation. Therefore, IoT middleware becomes important. IoT middleware can integrate heterogeneous resources and achieve bidirectional data communication and transmission between the sensing layer and decision making and application layer.

However, achieving the integration of management and control based on IoT middleware has become increasingly significant. Each command, resource property, and production event can be paired with a series of physical control addresses that are supervised and moderated by intelligent controllers (e.g., industry control computer, PLC). IoT middleware is a flexible and scalable solution for connecting, managing, monitoring, and controlling heterogeneous devices, and software applications. IoT middleware can also provide interoperability, thus allowing automation control information to be leveraged throughout an organization. For example, “Kepware Technologies” develops Kepserver,

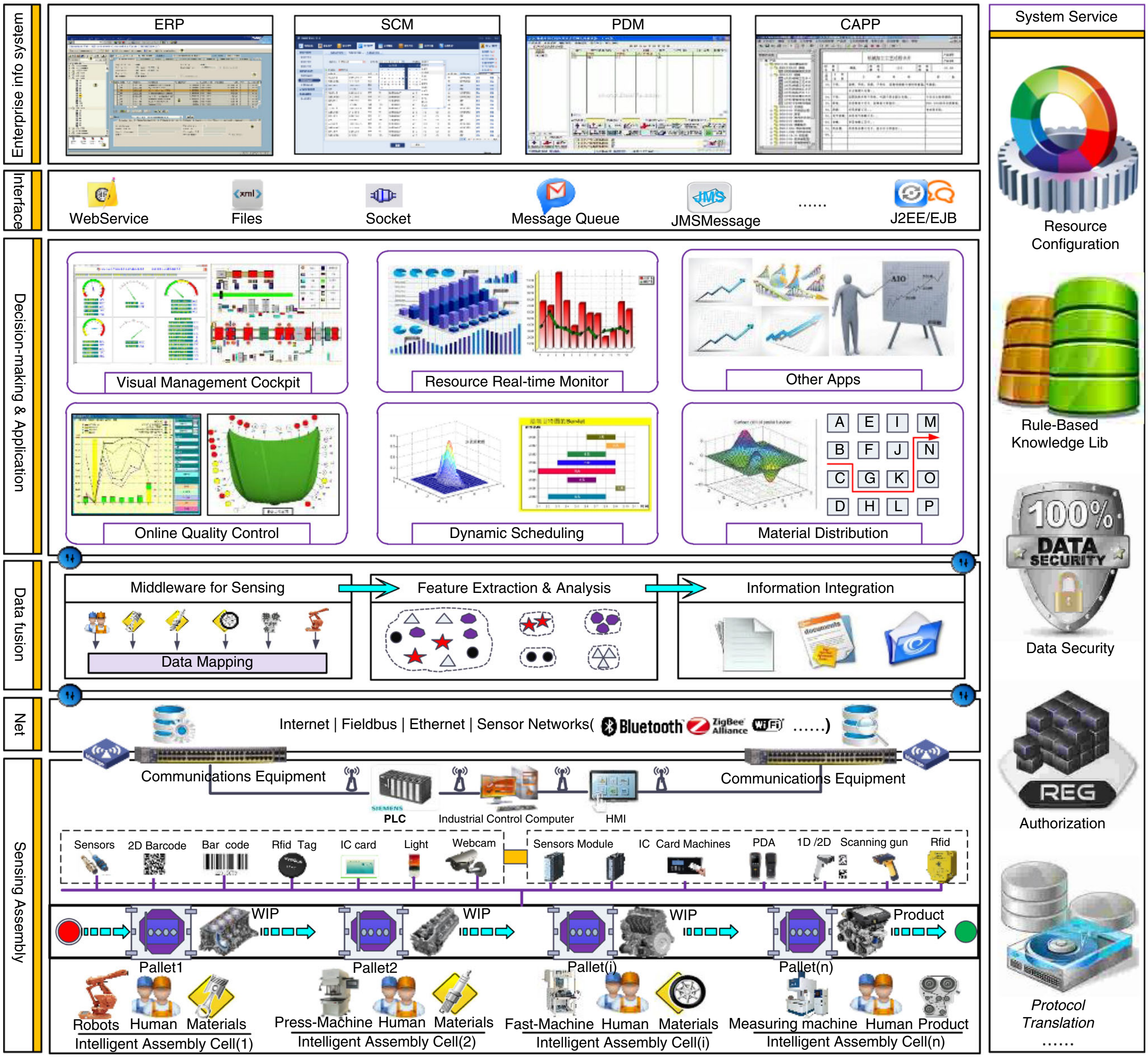

Fig. 1 Overall infrastructure of IIASMP

which offers a rich platform that holds an array of open standards, such as OLE for process control (OPC), propriety communication protocols, API, and various interfaces of automation systems (e.g., Siemens, Honeywell, Omron, Aromat, Mitsubishi, Toshiba, DNP, Yokogawa, and GE). Kepserver enables improved operations and decision making throughout all layers of an establishment. IoT middleware items can establish the mapping relationship between physical control addresses and assembly resources, i.e., IoT middleware simply specifies the data address and not as the actual physical data source that the address references.

The sensing assembly layer consists of a distributed control system (DCS), which can perform various tasks (e.g., resources sensing, recognition, and device control) independently. The IoT middleware provides interoperability between the sensing assembly layer and the decision making and application layer. Moreover, the IoT middleware can integrate DCS and achieve comprehensive sense, sharing, and cooperation.

Key enabling technologies

Manufacturing resource classification, resource modeling, and information encoding technology

Resource classification and encoding technology is used to ensure information semantic consistency in the product life cycle, which is the foundation and prerequisite of product information sharing. Therefore, the quality of resource classification and encoding directly affects product information sharing and exchange. Advanced technologies, such as computer and information technologies, sensors, and RFID, have been rapidly developed and widely deployed to assemble resources (e.g., material, equipment, personnel, energy). These technologies offer automatic and accurate resource data capture and enable real-time traceability and visibility. These key technologies simplify data parsing, exchange, processing, and sharing. Hence, normative resource classification and encoding have a positive effect on information processing and sharing. This section will be discussed from the following two aspects.

Feature mapping of the resource object set

In this section, feature mapping is divided into three types: basic, combined, and operating feature mapping. Figure 2 shows the feature mapping of resource objects.

Basic feature: Fig. 3 shows the basic feature mapping. Three levels are involved in the static feature of resources, namely, the resource category, sub-category, and basic information or content of the specific object. The first level defines four categories of resources: human, material, equipment, and other resources. The second level describes the resource object in the resource category. The last level presents the resource object information. For example, material resources contain the self-made material, outsourcing material, purchased material, standard material, and assembly objects. Each specific object has basic information, such as material number, name, classification, and shape.

Combined feature: This feature is the configuration relationship between one resource object and the other resource objects or operating rules of the resource. Three types of configuration modules are shown in Fig. 4: plant, product, and processes configurations. The plant configuration module aims to establish the relevance among the factory, assembly line, station, device, warehouse, and personnel. The product configuration module configures the relationship among the product bill of material, assembly routing, material, manufacturers, warehouse, and device at the processes configuration modules and the relationship among processes and other resource objects, such as process routing, process step, process station, process material, and process-quality standard.

Operation feature: The basic and combined features are the relatively static features of resource objects. The operation feature, which shows the dynamic operation status of resource objects, is proposed on the basis of the first two features (Fig. 5). Thus, this feature is an essential part of the resource object. With the constant input of resources and out-

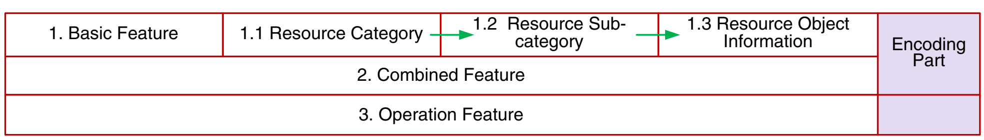

Fig. 2 Feature mapping of resource objects

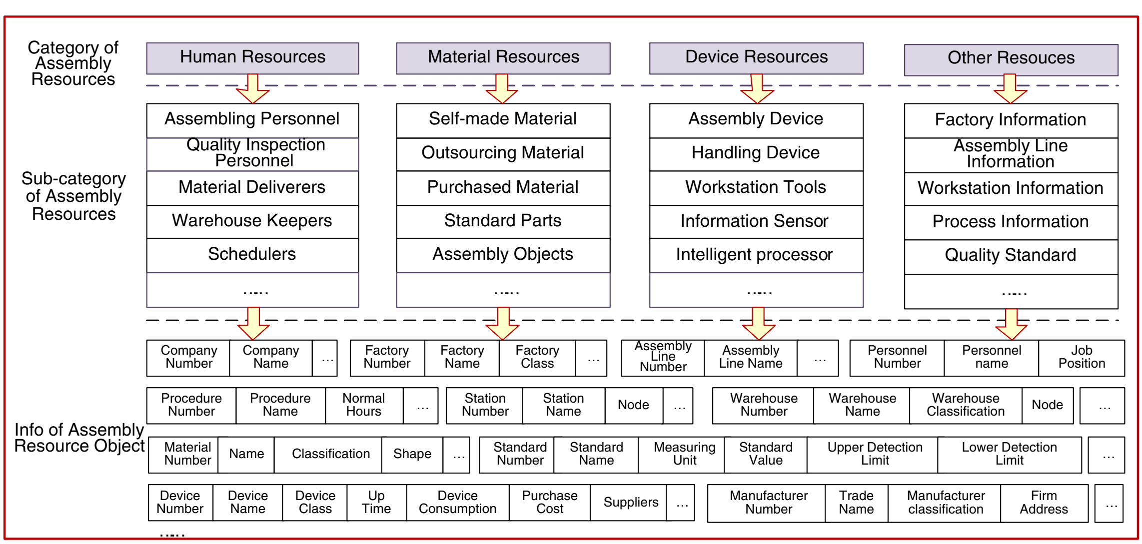

Fig. 3 Static features

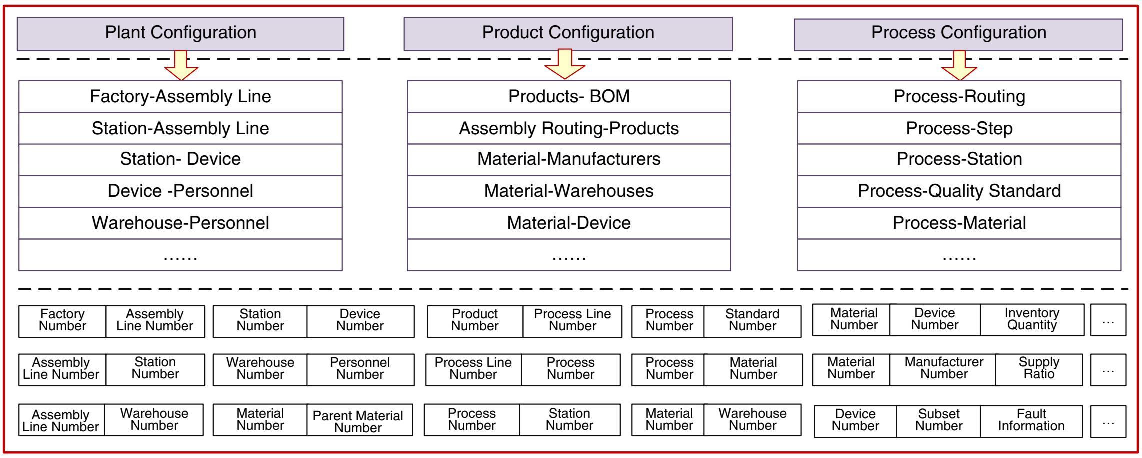

Fig. 4 Combined features

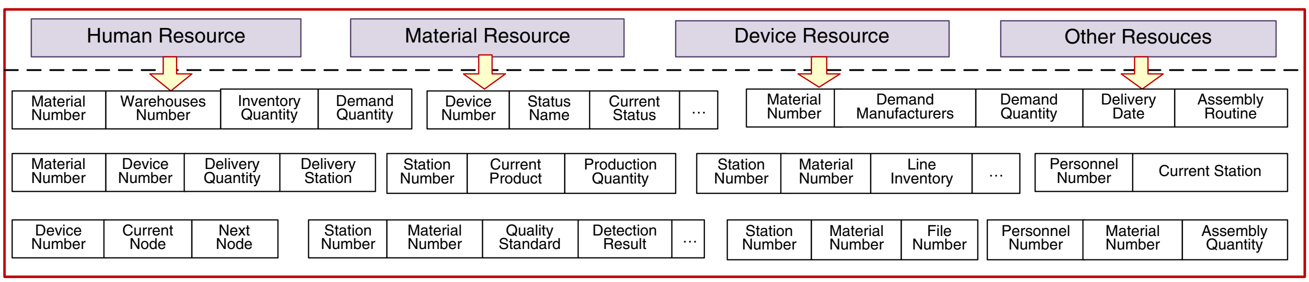

Fig. 5 Operation features

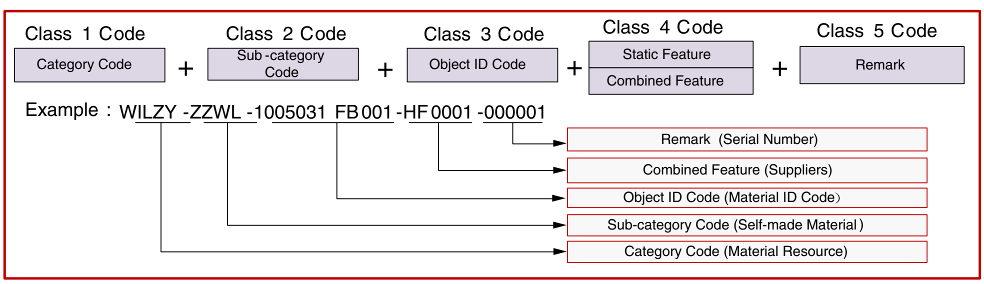

Fig. 6 Encoding structures of resource information

put of products, a management information system records the real-time information of the assembly processes on the basis of operation feature structure.

Resource encoding

The resource encoding technology links a resource object to the assembly processes and marks the resource features. Therefore, a unified and normative encoding system is the basis of accurate expression, transmission, and integration of information.

This paper uses five classes of codes to mark the resource information in Fig. 6. The first class is used for resource category. The second class represents the sub-category. The third class represents the identification code of a resource object; this identification code is unique and can be indexed. The fourth class represents the static and combined features of the object. The last class is used for some remarks.

Resource modeling

The manufacturing resource model is the premise and foundation to realize the goal of digital manufacturing. The expression form of the resource is data. Ontology is a computational model of some portions of the manufacturing system. This model is used to facilitate data interaction, sharing, and reuse, is often captured in a semantic network and represented by a graph, where nodes are concepts or individual objects and arcs represent the relationships or associations among the concepts (Lee et al. 2006). Ontologies are introduced as an "explicit specification of conceptualization." Conceptualization describes concepts inside their contexts unambiguously in a systematic manner. The specification of ontology is linked to the concrete ability to write and store knowledge in an optimal manner. This section takes assembly resources as the research object and proposes an assembly resource model on the basis of ontologies after analyzing the function of ontologies. The ontology-based assembly resource model will be introduced in the following sections.

Assembly resources can be divided into a meta-resource and combined resource. The meta-resource $DeSu_i$ is the basic resource unit of assembly and could be represented by its attributes $DeSu_i$ ::= {*ob-type*, *obj-name*, *obj-id*, *obj-address*, *obj-pa*, *obj-pro*, *obj-provaule*, *obj-sta*, *obj-rela*, *obj-res*, *obj-other*}, where "*ob-type, obj-name, obj-id*, and *obj-address*" represent the type, name, identification, and physical control address of the meta-resource, respectively. "*obj-pa*" represents the meta-resource parent resource (combined resource) and its properties. "*obj-pro, obj-provaule, obj-sta, obj-rela, obj-res*, and *obj-other*" represent the meta-resource property collection, property values collection, meta-resource state, relations collection, constraint set, and other features, respectively. The combined resource $Com\text{-}Su_i$ consists of a meta-resource and combined resource under certain constraints and requirements that can be subdivided and combined. $Com\text{-}Su_i = \{DeSu_1, DeSu_2, \ldots, DeSu_n, Com\text{-}Su_1, Com\text{-}Su_2, \ldots, Com\text{-}Su_j\} (i = 1, \ldots, n), (j = 1, \ldots, m)$. $Com\text{-}Su_i$ ::={*com-name*, *com-id*, *com-address*, *com-type*, *com-pa*, *com-sta*, $\sum DeSu_i$, *com-re*}, where "*com-name*, *com-id*, *com-address*, and *com-type*" represent the name, identification, physical control address, and type of combined resource, respectively. "*com-pa*" represents the parent resource of the combined resource, and "*com-sta* and *com-re*" represent the state of the combined resource and the relations collection for the meta-resource, respectively. "$\sum DeSu_i$" represents the meta-resource collection, which also includes the combined resource. The combined resource state is *com-sta*: : ={*com-failure*, *com-leisure*, *com-halfload*, *com-fullload, com-overload*}, where *com-failure*, *com-leisure*, *com-halfload*, *com-fullload*, and *com-overload* represent the combined-resource failure, leisure, half-load, full-load, and over-load state, respectively.

Some markup languages (e.g., XML, physical markup language (PML), and OWL) define a set of rules for encoding information in a format that is both human readable and machine readable and offer a complete framework for ontology reading and writing. These languages are rapidly evolving toward the standard for data integration and exchange over the Internet and within intranets, thus covering the complete spectrum from largely unstructured ad hoc documents to highly structured schematic data. The markup languages will be introduced in "Information interaction technology" section. Several application programming interfaces have been developed to aid software developers in processing markup language data. Figure 7 shows an example of ontology based on the proposed resource model.

Information interaction technology

Data interaction format

Data interaction is a prerequisite to achieve real-time, seamless dual-way connectivity and interoperability in an intelligent assembly system. Various formats (standards) are used for information interaction in an intelligent assembly system, where packet, XML, record columnar file (RCFile), and PML for IoT are classic format.

A packet is the elementary unit of data interaction and transmission. The data are encapsulated once as a data block according to the protocol and is then transmitted as a block. XML is a markup language that defines a set of rules for encoding documents in human- and machine-readable formats. RCFile is a hybrid data-placement structure that combines the row-storey structure and column-storey structure. In a relational database, data are organized as 2D tables. To serialize the table, RCFile first partitions the table horizontally and then vertically. Horizontal partitioning first partitions the table into multiple row groups on the basis of row-group size, which is a user-specified value that determines the size of each row group. Horizontal partitioning has fast data loading and strong adaptive ability to dynamic workloads. Thereafter, in every row group, RCFile partitions the data vertically similar to a column-store for fast query processing and efficient storage space utilization. PML is a markup language based on XML and is used for communicating the description of physical environments, the objects in the environments, and their relationships between each other. PML provides a standard vocabulary to represent and distribute information about Auto-ID-enabled objects. AutomationML is a neutral data format based on XML for the storage and exchange of plant engineering information. AutomationML facilitates the data exchange between manufacturing engineering tools and supports the interoperability between them. AutomationML covers information about plant structure (topology and geometry) and behavior (logic and kinematics). The first version of AutomationML has been presented at the 2008 Hannover Fair (Drath et al. 2008).

Data interaction standard

The step application protocol alone does not solve current enterprise interoperability problems. To achieve data interaction, each stakeholder has its own nomenclature and asso-

DeCom-Su: Workstation


```
<?xml version=" 1.0" ,Encoding=" GB2312" ?>
<DeCom-Su_i>
    <com-type>workstation</com-type>
    <com-name>bolt tightening of cylinder </com-name>
    <com-id>OP105</com-id>
    <com-pa>
        <com-type>assembly systems</com-type>
        <com-name>cylinder assembly system</com-name>
        <com-adress>192.168.1.1-192.168.1.10<com-adress>
    </com-pa>
    <com-pro>
        <com-pro1>process function</com-pro1>
        <com-pro2>detection limit of torque </com-pro2>
        <com-pro2>detection limit of angle </com-pro2>
    </com-pro>
    <com-provaule>
        <com-provaule1>bolt tightening of cylinder</com-provaule1>
        <com-provaule2>[14.2 ,15.3 ]NM</com-provaule2>
        <com-provaule2>[89.2 ,91.3 ] °</com-provaule2>
    </com-provaule>
    <∑DeSu_i>
        <∑DeSu_1>PLC</∑DeSu_1>
        <∑DeSu_2>RFID、scanning guns</∑DeSu_2>
        <∑DeSu_3>torque &angle  sensors</∑DeSu_3>
        <∑DeSu_4>RFID tags、alarm lights</∑DeSu_4>
        <∑DeSu_5>servo motors</∑DeSu_5>
    </∑DeSu_i>
    <com-sta>com-fullload</com-sta>
    ……
</DeCom-Su_i>
```


DeSu:materials


```
<?xml version=" 1.0" ,Encoding=" GB2312" ?>
<DeSu_i>
    <obj-type>material</obj-type>
    <obj-name>cylinder </obj-name>
    <obj-Id>01018634HF-C3D0130606001</obj-id>
    <com-Pa>
        <com-type>product</com-type>
        <com-name>1.5 L Engine</com-name>
        <com-id>01256230HF-C3D0130606001</com-id>
    </com-pa>
    <obj-pro>
        <obj-pro1>safety stock</obj-pro1>
        <obj-pro2>real-time stock</obj-pro2>
        <obj-pro3>supplier name</obj-pro3>
        <obj-pro4>supplier code</obj-pro4>
        <obj-pro5>torque  value</obj-pro5>
        <obj-pro6>angle value</obj-pro6>
    </obj-pro>
    <obj-provaule>
        <obj-provaule1>20</obj-provaule1>
        <obj-provaule2>19</obj-provaule2>
        <obj-provaule3>Huiteng</obj-provaule3>
        <obj-provaule4>S-DLHT001</obj-provaule4>
        <obj-provaule5>14.6</obj-provaule5>
        <obj-provaule6>90.3</obj-provaule6>
    </obj-provaule>
    <obj-sta>material shortage</obj-sta>
    <obj-res>pre-workstation </obj-res>
    ……
</DeSu_i>
```


Fig. 7 Example of ontology-enabled resource data model

ciated meaning of its business products. Therefore, the data exchanged may still be misunderstood by all business partners despite sharing the same structure (Jardim-Goncalves et al. 2011). Cutting-Decelle et al. (2007) present the ISO 15531 MANDATE standard for the exchanges of industrial manufacturing management data. A data interaction framework in smart assembly system is proposed on the basis of the data interaction standard provided by the Rockwell Factory Talk Production Center (FTPC) platform (Fig. 8). Four core modules are involved in this framework to implement data interaction: basic specification, generation and compression of data block, storage and interaction of data block, parsing, and application of data block.

The basic specification module provides information encoding and the interaction standard. This module mainly contains two components, namely, the resource information-encoded library and the data interaction protocol and standards. The generation and compression of data block are based on the basic specification and interaction request. In this module, the perception data are packaged and compressed by the data block generator and then sent to the block storage and interaction area.

In the storage and interaction of the data block module, synchronous data interaction is combined with asynchronous data interaction to achieve client–client online and offline data block transmission. In the analysis and application of the data block module, the client uncompresses and parses the data block on the basis of basic specifications. The data are then converted to information through the man–machine interaction system. The information is further used in system application and decision making.

Multi-source data perception, and fusion technology

This key technology uses advanced technologies (e.g., RFID, barcodes, and sensors) to sense the assembly resources and their condition. Feature extraction and information integration are then used to achieve sensor data fusion via the sensing middleware. Finally, the integrated information can directly support the applications and decision making. Figure 9 shows the framework of such technology. The three layers involved in this framework are the intelligent assembly resource layer, physical sensing layer, and fusion layer.

Multi-source data perception technology

Advanced technologies have been widely used in the production system. Capturing the real-time information of the assembly resources is necessary for the transparency of assembly processes. Personnel, machines, materials, and

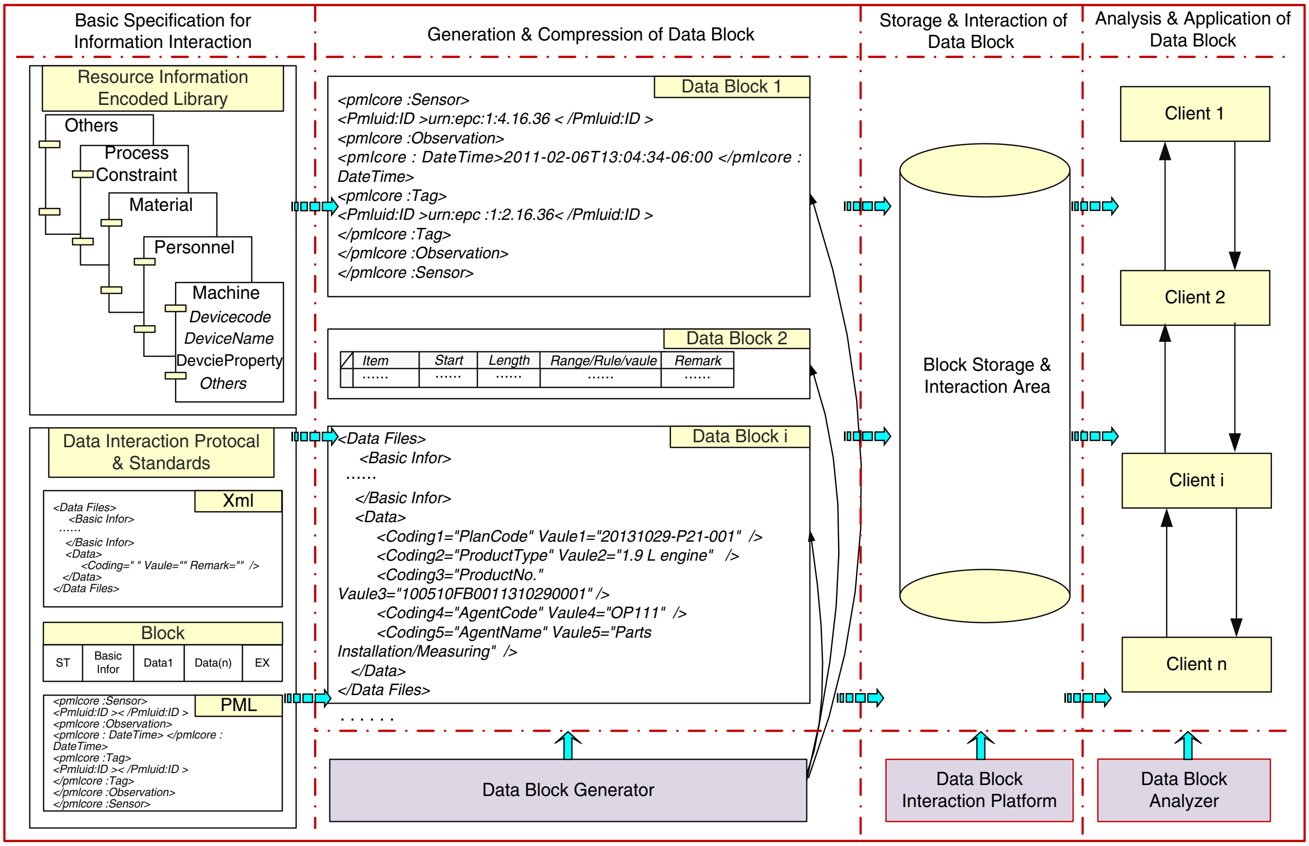

Fig. 8 Data interaction framework

other assembly resources are usually equipped with RFID tags, barcodes, sensors, global positioning systems (GPSs), and visual devices to identify shop-floor objects and their conditions via RFID readers, scanning gun, PLC, computers, and servers and achieve data physical sensing. The advanced technologies are used in several ways.

1. Materials, pallets for holding WIP, and products are attached with RFID tags and barcodes. These intelligent assembly resources can be identified by RFID readers, scan guns, and personal digital assistant devices. Operators are usually equipped with identity cards that can be used to boot machines and operate system modules by using their authorized card. For example, a pallet equipped with an RFID tag offers information storage and communication functionality to automatically capture the unique serialized shipping container code of the pallet at relevant reading points.
2. Physical sensors, optical sensors, vision sensors, and other sensors are usually deployed at assembly stations to complete different functions. For example, the proximity switch is used to sense a pallet at assembly stations. A photoelectric switch is used to sense whether a pallet holds materials. A vision sensor is applied with operation research to capture the real-time motions of operators; the collected motions are then sent to the processor for image matching with the defined and standard motions. Finally, the processor decides whether the operator is in the danger zone and the motions of the operators are standard.
3. Product quality is essential for enterprises. Therefore, measuring machines must be used for quality control. The most common resolution to date is to equip measuring machines with special sensors. For example, torque, pressure, and temperature sensors are used to monitor the tightening force, pressing force, and temperature values of bolts.
4. Material-handling devices can also be equipped with orientation sensors and GPS to achieve material delivery and device localization.

Sensor data fusion technology

The principal objective of multi-sensor data fusion is to improve the quality of information output in a process known as synergy, which is widely used for combining sensor data or data derived from sensory data into a common representational format to improve system performance in four different

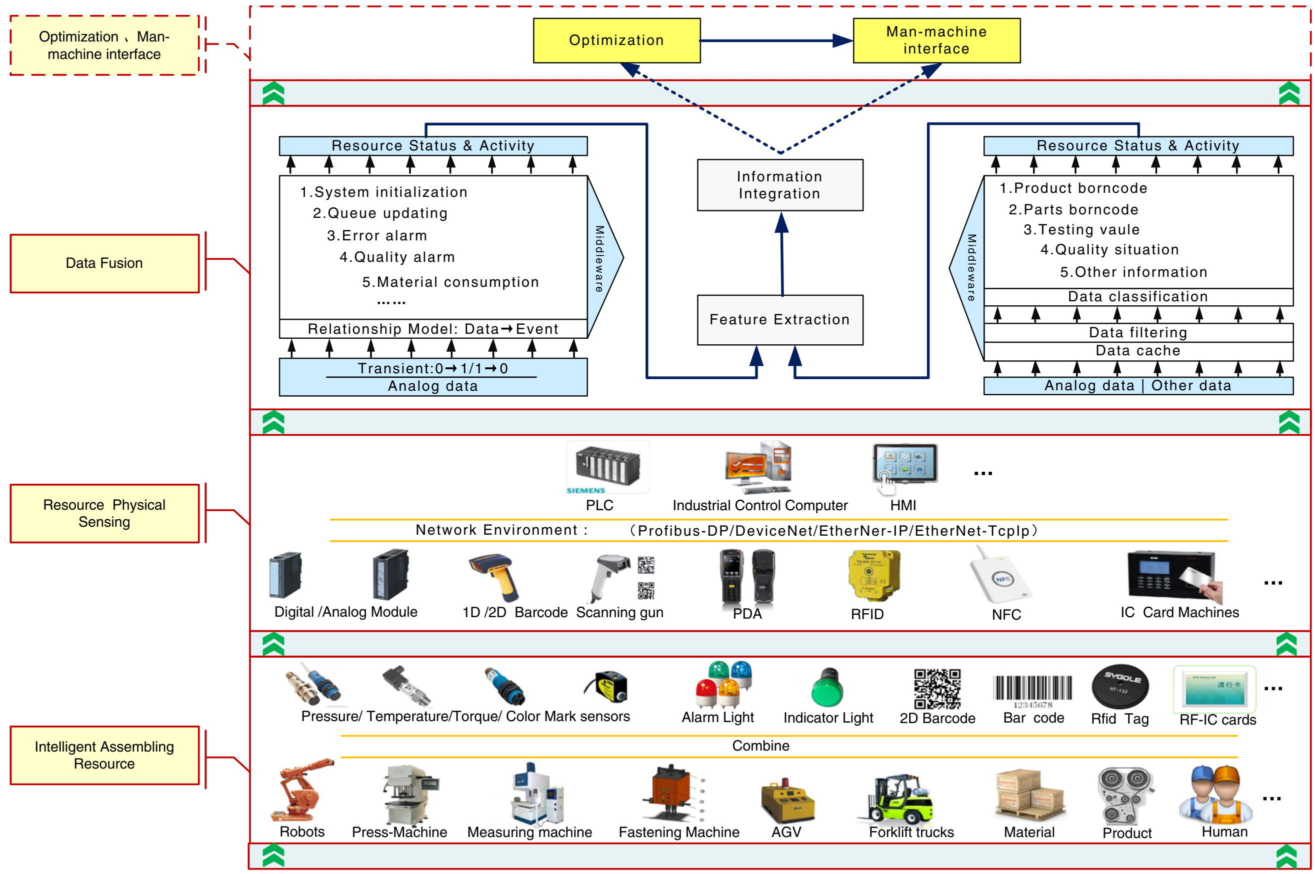

Fig. 9 Multi-source data perception and fusion framework

methods: representation, certainty, accuracy, and completeness (Mitchell 2007). Different types of equipment have different data capturing standardization, thus directly resulting in heterogeneous and uncertain data. IoT middleware, feature extraction, and information integration methods have been proposed in this section to convert data to certain and unified information. Figure 9 shows the sensor data-fusion process.

IoT middleware: The IoT middleware has been mentioned in “Overall framework of IIASMP” section (interoperability between variety layers) and aims to link the resource objects to their sensed data and helps convert data. Relevant technologies and standards (e.g., opening and interoperable interface standards, object linking, and embedding technology) are widely used to resolve heterogeneous data adaptation and interaction problems. OPC is the first automation-domain-specific component standard that consists of a set of standard COM objects, properties, and methods for different device communications in manufacturing processes control. OPC offers a uniform access to data in the industrial field. The following key portions are involved in sensing middleware:

1. Data Address Mapping. This paper first focuses on data address mapping among devices connected to the middleware software (e.g., NI Measurement Studio, Sysmac OPC Server, Simatic OPC Server, and Kepserver).
2. Address-Object Mapping. In the shop floor, the directly sensed data are heterogeneous and uncertain. The data address should be linked to the assembly resource objects and production events for the data to become meaningful.
3. Resource Encoding. The system cannot easily understand complicated production data; thus, the encoding system is essential for data parsing. The encoding system mainly contains code overall length, class, length, start bit, and stop bit for each class.
4. Data exchange. IoT-middleware-enabled engineering software runs on the operating system and can capture real-time manufacturing data from heterogeneous devices indirectly.
5. Data Parsing and Conversion. On the basis of address-object mapping, the system can understand manufacturing data immediately. Thus, the sensing data become meaningful and can be related to specific events and objects.

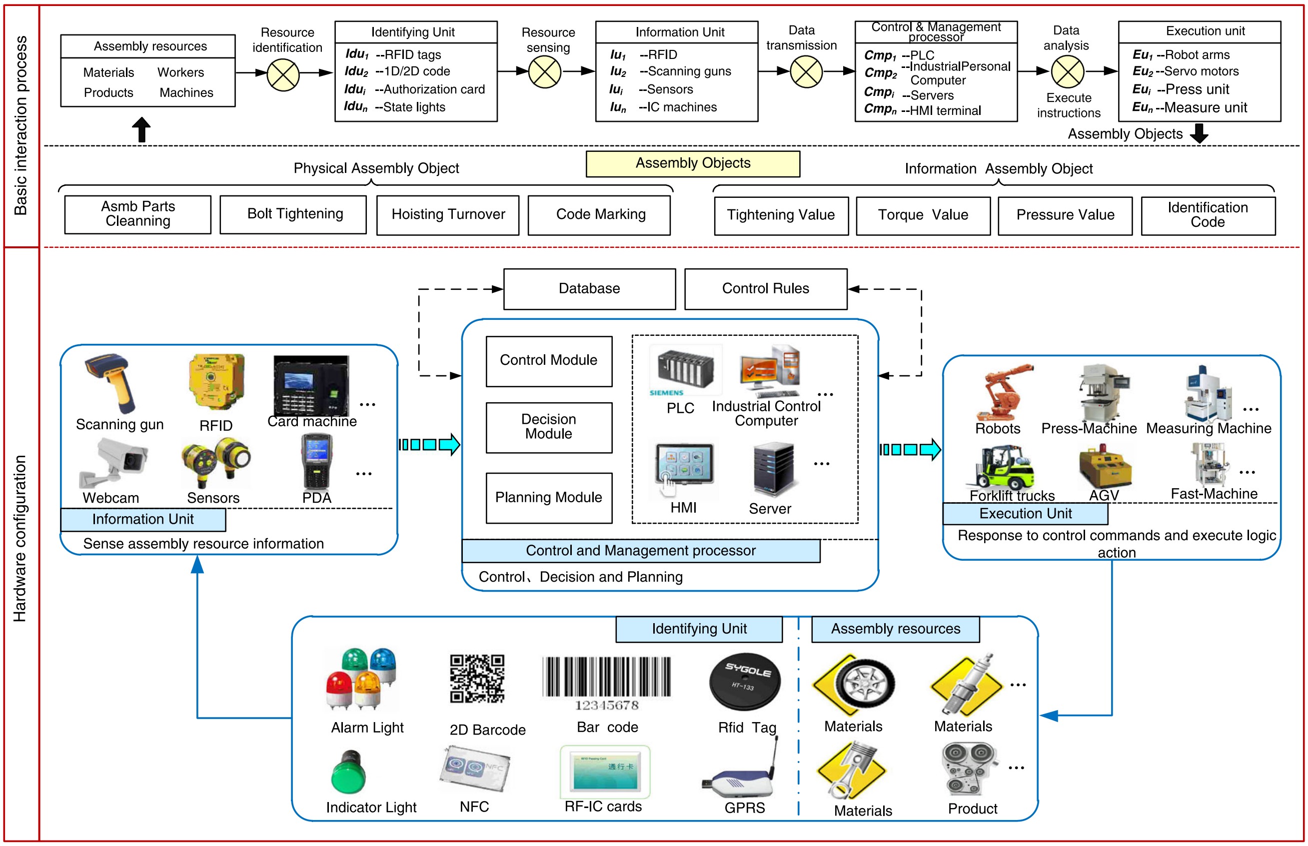

Fig. 10 Intelligent assembly agent

Feature extraction: This method transforms large amounts of sensed data into feature sets to filter redundant information without losing sufficient accuracy, thereby reducing information conflict and information integration difficulty.

Information integration: Open-object-oriented technology is adopted and unified. A normative encoding system is then used to cluster and regroup information, thus forming a uniform information representation and realizing information integration and sharing in the system.

Intelligent assembly agent

The increasing market competition intensifies the transformation of the production mode. Therefore, to succeed in this environment, many enterprises are in urgent need of highly flexible, distributed, and smart production systems to cope with such problem. An agent is an active object that possesses certain capabilities to perform tasks and communicates with other agents on the basis of the organizational structure to accomplish tasks (Chen and Tu 2009). Chen (2012) adopted the Petri net method to construct a cell controller model and then employs a modular design to develop an FMS cell controller on the basis of RFID. Various agent-based methodologies on production management and control are now used in enterprises, such as intelligent agent-enabled manufacturing system and multi-agent-based system for manufacturing control.

This study proposes an intelligent assembly agent for the self-organization, self-adaptation, self-studying, and self-maintenance of dynamical manufacturing processes. This study considers an intelligent assembly agent as a manufacturing unit that can sense the assembly environment, perform various assembly actions, monitor its own status, and communicate with other assembly units. The agent is an important part of the production system. Figure 10 shows the framework of an intelligent assembly agent that consists of a sensor unit, execution unit, management and control processor, and knowledge library. Figure 10 also shows the related parts of the smart assembly agent.

The assembly object contains two objects: physical and information assembly objects. The physical object is visible and is used to perform tasks under production commands, such as bolt tightening, parts assembly, and product capability test. By contrast, the information assembly object is invisible and instructs the equipment to accomplish tasks, such as production planning, process routing, and acceptable range of quality value.

Five key components with different individual functions are involved in the intelligent assembly agent: identifying unit (*Idu*), information unit (*Iu*), control and management processor (*Cmp*), execution unit (*Eu*), and knowledge library. The *Idu* can make some assembly resources be perceived to achieve resource identification. *Iu* can perceive an identifying unit and themselves. On the basis of the comprehensive sense, transmission, and sharing, *Cmp* can conduct data analysis and control *Eu* to achieve both physical and information assembly objectives. The basic interactive process of each intelligent assembly agent is as follows:

1. Identifying Unit. This part mainly addresses the sensing of normal assembly resources (e.g., materials, WIP, product, and material-handling devices) by the information unit. The general approach is to attach some identifying units (e.g., RFID tags, barcodes, GPS, and IC cards) to the assembly resources. These identified resources can be sensed and recognized by some information units (e.g., RFID, scanning guns, and IC machines). Therefore, on the basis of the identified resources, some information units can collect resource data and capture abnormal production data automatically.
2. Information Unit. Humans have five senses, namely, sight, hearing, smell, taste, and touch, to capture environment information and support decision making. The information unit (e.g., RFID readers, scanning guns, card machines, and sensors) has perceived capacity. The information unit is similar to the human senses used to sense heterogeneous data from the identifying unit and assembly environment, which triggers the corresponding management and control events according to the sensing data. The sensed data are mainly workstation, material, product, equipment, and workers. For example, proximity switch is used to judge the pallet state (arriving or leaving). A photoelectric sensor is applied to sense whether the pallet is empty. An RFID is used to obtain the product data chain stored in the RFID tag. Scanning guns are used to collect material data, which contain the supplier's name, code, and batch number. Machine vision is mainly applied for defect inspection. Other sensors (e.g., torque sensor, angle sensor, and pressure sensor) are usually used for quality testing and fault detection. All heterogeneous data are directly used to support decision making and other uses.
3. Control and Management Processor. The management and control processor is like the brain of the agent. This process is the key component of an intelligent assembly agent and guarantees the agent performance, such as PLC, server, and industrial control computer. This process mainly includes three functional modules, namely, control, planning, and decision modules. Under the interactions of the modules, the sensed data are processed from the information unit to output some instructions, and then send the instructions to the execution unit. An example of *Cmp* function is already shown in "Definition and characteristics of IIASMP" section (self-regulation and self-organization).
4. Execution Unit. The execution unit is like the limbs of the agent. This process is used to respond to management and control instructions or assembly (action) instructions, such as the welding robot, fastening machine, pressing mechanism, measuring equipment, and material-handling device.
5. Knowledge Library. The knowledge library is the foundation of the intelligent assembly agent and provides knowledge storage, knowledge retrieval, resource decoding rules, agent control rules, strategy computing model services, and an image library.

Each agent (workstation) includes an input buffer (I-buffer), operation area, and output buffer (O-buffer). Appropriate buffers can improve the production line balance rate. The I- and O-buffers are used to store the agent input and output pallets, respectively. The operation area is used to complete the assembly objective. Therefore, a bolt tightening agent will be introduced in this study to further illustrate how the assembly intelligent agent works (Fig. 15). All steps are completed by the intelligent assembly agent automatically.

Value-added data

In modern manufacturing, the data volume increases at an unprecedented rate in digital manufacturing environments by using barcodes, sensors, vision systems, and so on. However, the use of accumulated data are limited, which has led to the "rich data but poor information" problem (Wang and McGreavy 1998). Hence, data mining technology has emerged as an important tool for knowledge acquisition from manufacturing environments. The major data mining functions to be performed include characterization and description, association, categorization, prediction, clustering, and evolution analysis (Choudhary et al. 2009).

Given the wide use of comprehensive data sensing technology in the assembly system, the demand for a modern technique to process the large influx of sensing data has increased. In this particular case, value-added data are the proper technique to take on the challenge. Value-added data technology mainly includes two phases. The first phase is based on real-time perceptual data. This phase aims to convert sensing data to certain information and support manufacturing systems to complete basic functions. The second phase is knowledge discovery from databases (KDD). Databases contain large numbers of records with many attributes that need to be simultaneously explored to discover use-

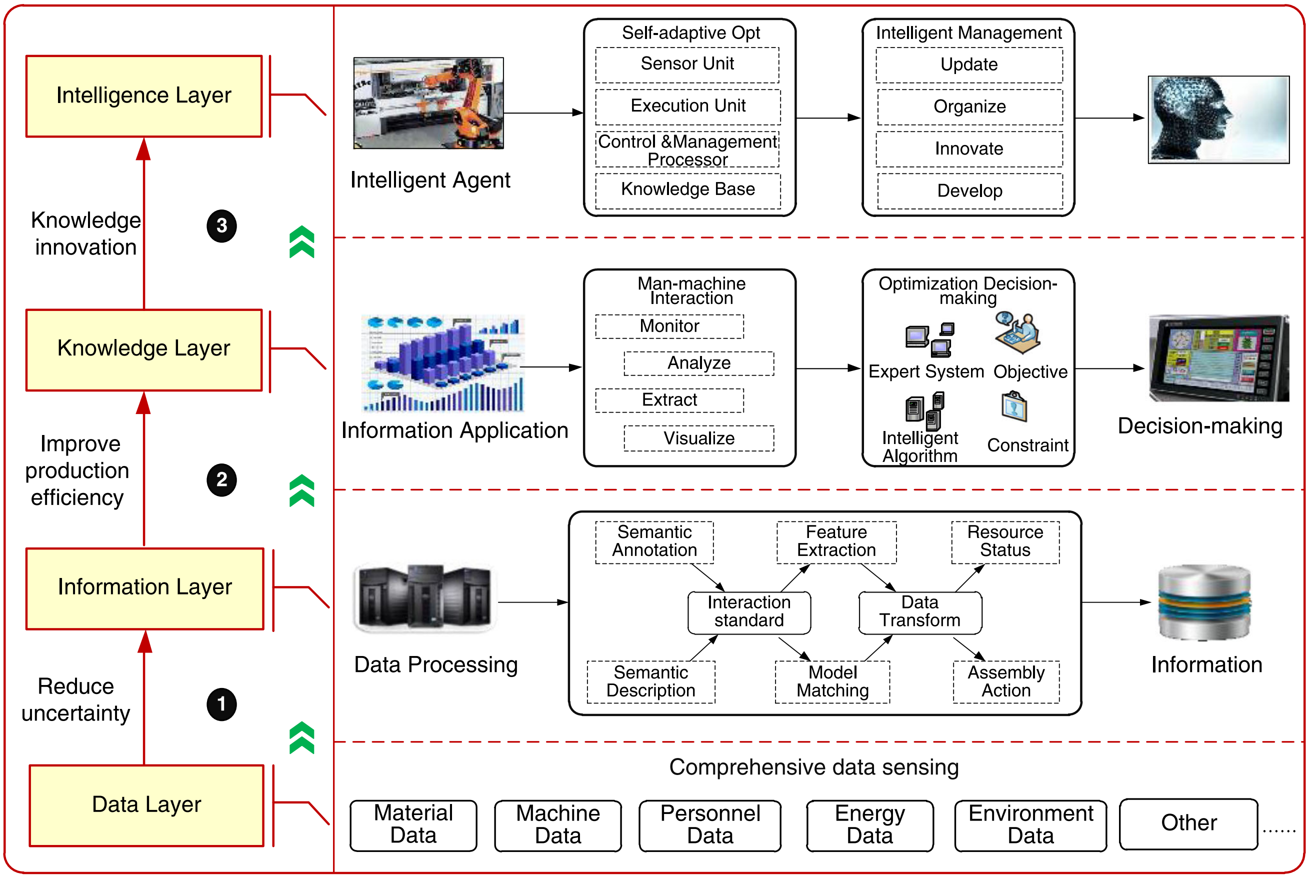

Fig. 11 Value-added data framework

ful information and knowledge, thus making manual analysis impractical. The KDD process is knowledge intensive, and all steps require domain-specific knowledge (ontology). As a kernel step of KDD, ontologies can help data mining to be effective, innovative, and efficient (Choudhary et al. 2009). Ontology can drive knowledge maintenance and assist query formulation, active data mining, and online mining (Tseng and Lin 2001). Ontology formally defines a common set of terms to describe and represent domain knowledge. Ontology also provides a set of definitions of content-specific knowledge representation primitives: classes, relations, functions, and object constants. Therefore, the characteristics of ontology technology has been widely applied to data mining.

In this section, data mining, man–machine interaction, intelligent algorithm, dynamic self-adaptation, and intelligent agent technologies are adopted to achieve value-added data. Digging into the nature of assembly performance and understanding the reason of assembly information are the goal of value-added data. The value-added data framework is shown in Fig. 11. Three stages are involved in the framework to complete the value-added data.

1. The first stage transforms data as information or minimizes data uncertainty. Data features are extracted, the matching model to process the data is identified, and the data are transformed to useful resource status information and assembly action information through semantic annotation, description, and interaction protocol. This stage mainly aims to complete the basic function of data mining (e.g., characterization and description) and is divided into three processes. First, the IoT middleware can integrate heterogeneous resources and achieve bidirectional data communication and transmission between the manufacturing execution and decision layers ("Multi-source data perception, and fusion technology" and "Overall framework of IIASMP" section). Second, on the basis of the ontology-enabled resource data model proposed in "Resource modeling" section, some of the semantic methods (e.g., XML, PML, and OWL) can be used to write and store data in an optimal manner. Finally, based on the general data expression of the manufacturing resource, perception data will be packaged, compressed, and used for interaction according to the interaction standard discussed in the previous section.

2. The second stage mainly performs some data mining functions (e.g., association, categorization, prediction, and clustering). This stage allows information to become useful knowledge and supports the operation of the manufacturing system. Some of the real-time information is directly used to instruct online operations (online data mining), whereas other information are stored and used for KDD. The man–machine interaction technology and optimization decision-making technology are used in this stage. The system will monitor, analyze, extract, and visualize the manufacturing on the basis of real-time information (online data mining). According to the optimization objective and constraints, the system can use expert system and intelligent algorithms to obtain KDD, which is further researched and widely used.
3. The last stage allows knowledge to become intelligence (evolution), which is one of the primary goals of data mining. Evolution is the highest level of data mining and the hardest to achieve. On the basis of achieving evolution, the manufacturing system is self-adaptive and can be improved by using the sensor unit, execution unit, control and management processor, and updated knowledge library. Therefore, the intelligent system can be developed and evolved.

Dynamic self-adaptive optimization

Given the high complexity of the assembly process and numerous influencing parameters, the assembly process shows a nonlinear dynamic behavior. To cope with this problem, research and development of optimal methods for assembly systems are necessary. To date, modern process optimal methods are driven by massive sensing data, urgent demand for product quality, high manufacturing process safety, minimal costs, and short production cycle. Some research results indicated that dynamic optimization is the core characteristic of IMS.

In summary, the implementation of optimization techniques within production processes is necessary for enterprises to respond effectively to international competition and changing demands. The dynamic self-adaptive optimization model is proposed in this paper to represent optimization processes in a model. The model for dynamic self-adaptive optimization is shown in Fig. 12. The model has seven parts: sensing network, bi-direction data transfer, information processing, decision making and optimization part, self-adaptive dynamic optimization model library, visual management cockpit, and decision maker and optimization servers. The self-adaptive dynamic optimization model library contains related models for different assembly businesses: production scheduling, personal scheduling, material distribution, assembling tolerances, and control policy. Six steps are conducted to complete the self-adaptive dynamic optimization.

1. Determine the optimization objective. The analyzer obtains the dynamic optimization variables according to the objective, and then sends these values to the controller. These variables are parsed on the basis of predefined(e.g., production scheduling, personal scheduling, material distribution, assembling tolerances, and control policy) and custom factors sets.
2. Send model and instruction. The controller first sends the call instruction to the library for model matching. Thereafter, the variable, constraints, and matching model are sent to the model processor.
3. Integration, transfer, and execution. The model processor obtains the global optimal instruction on the basis of incoming variables, constraints, and matching models. Subsequently, the interface adapter transmits the instruction to the executive signal identified by the corresponding intelligent agent (e.g., assembly agent, material delivery agent) to drive machines to work and achieve optimization.
4. Sensing and transmission. The sending unit in the intelligent agent collects the real-time assembly process data. These data are translated into certain and meaningful data by a sensing middleware. Subsequently, data are transferred to the value-added data module. The value-added data go to the analyzer for further processing as feedback information after filtration and extraction.
5. Obtain optimal solution. Obtain the optimal solution to meet the optimization objective. The analyzer understands the relevance between the optimal instruction and the feedback information. The optimal solution is obtained from the relevance and intelligent algorithm library. The solution is then sent to the visual management and control cockpit (VMCC).
6. Decision making and iteration. The use of the configured primitive enables the optimal solution from Stage 5 to become a visual solution in VMCC. The cockpit helps the decision maker and optimization servers understand the difference between the actual status of the system and the estimated status. The decision maker amends the optimization objective according to the difference. The amendment goes to Stage 1. The whole process is iterated to improve the system continuously.

Material delivery is a dynamic process wherein the numbers and types of material deliveries are directly affected by causes (e.g., defect numbers of WIP and materials, emergency production scheme, and production quantity). Consequently, the pre-scheme of material delivery does not usually meet the actual demand of the manufacturing system. A dynamic opti-

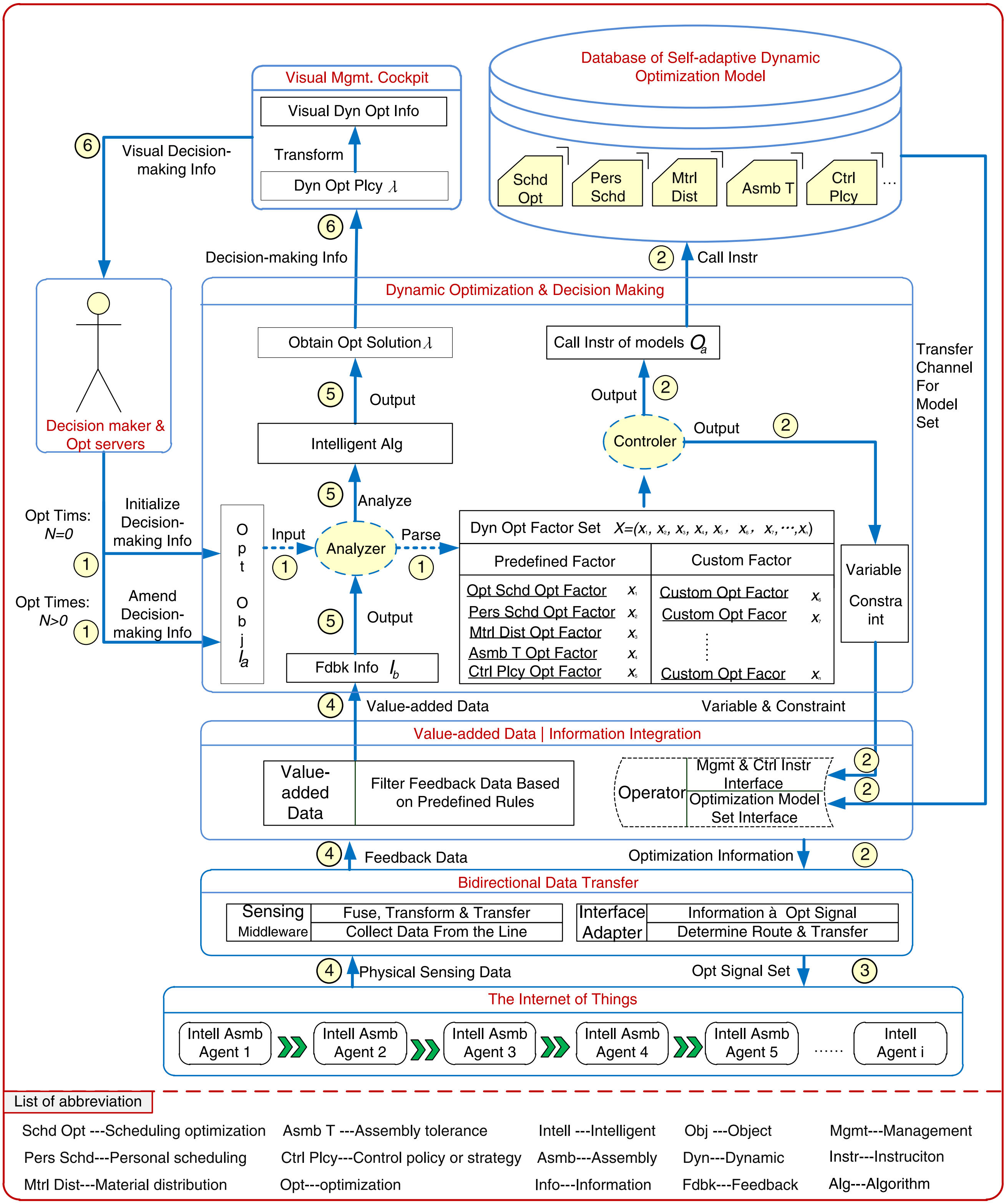

Fig. 12 Dynamic self-adaptive optimization model

mization case for material delivery is introduced on the basis of real-time sensed information to resolve this problem.

The material delivery event can be triggered by two ways. One is trigger by workers who are tasked to press the material button (e.g., software and physical buttons) and call material delivery. The calling signals are mapped and converted to a certain information immediately once the event occurs. Subsequently, the material call will be transferred to the top level for the analysis of material requirements (e.g., types, number, and workstation). Finally, the material requirements are displayed in the VMCC. Material handlers immediately handle this request and deliver the required materials to the corresponding workstations according to the visual decision-making information. The inventory threshold can also trigger the material delivery event. A model for determining the precise inventory of each assembly agent is proposed on the basis of the analysis of the causes. This type of material delivery is different, complex, and contains the following steps.

Step 1: The enterprise checks the inventory and conducts financial accounting at the end of each production period (e.g., month, quarter). Therefore, WIP is not allowed in this step. Subsequently, material handlers will reset the material delivery objects and invoke the function model (e.g., calculation formula) at the beginning of each production period to calculate and output a material delivery plan (material types, number, and work stations).
Step 2: The delivery plan is converted into physical signals (e.g., coordinates of shelves, number of materials), which can be received, recognized, and conducted by the intelligent warehouse that consists of materials, high storey shelves, stacker, multi-sensor, controller, etc. The materials are picked up by a smart stacker after receiving the signals, then the stacker places the materials on AGV (material-handling agent) for delivery.
Step 3: Some causes affect the pre-scheme of material delivery in the dynamic production process directly. Hence, decision maker or optimization servers amends the delivery plan to achieve just-in-time production. The first step is to collect volatile data from each assembly agent because delivery plans change with the fluctuations of affective factors. Each assembly agent is equipped with HMI, RFID, vision sensor, etc. An RFID is used to record and count the number of assembled and scrapped WIPs. A vision sensor is applied to recognize materials, count real-time inventory, and scrap agent material, which can also be entered by workers through HMI.
Step 4: Some pre-defined mathematical formula are used to calculate the actual demand of materials on the basis of the data conversion and information transmission. The actual material requirements are displayed in the VMCC. Material handlers or optimization servers amend the delivery plan according to the visual decision-making information. The whole process is iterated from Stage 2 to improve the system continuously.

Although this optimization method is characterized by dynamism and self-organization on the basis of real-time perceptual information, this method also has limitations. The performance of the method depends primarily on several key factors. The most important factor is the comprehensiveness of the optimization model (algorithm). Building optimization models that cover the entire production process is difficult. At present, the decision maker plays an important role in amending delivery plans. Optimization servers cannot make decisions by itself completely.

Interfaces with different level systems

Three principle types of production exist in the manufacturing industry. Each of these types has a knowledge representation level (e.g., PDM, PLM), horizontal integration level (e.g., SCADA, MES,), and production facility level (Saenz de Ugarte et al. 2009 and Kletti 2007). Each level interacts with each other. Some ordinary interface technologies (e.g., files, web service, sockets, message and database) have been proven possible in some research and application. Therefore, an intelligent system should keep some of the interfaces open. Interfaces function as connecting links between different systems and monitor the exchange of data when business and instruction data are received, when the actual data changes, and when corrections are returned. The proposed IIASMP mainly focuses on the assembly process of mechanical products. IIASMP interacts with each of the system levels via the existing interface technologies. Figure 13 shows the interfaces of IIASMP with the different system levels. Three types of interfaces are introduced as follows:

Interfaces with high-level systems (e.g., PLM, PDM): Business and instruction data (e.g., production planning, material planning, bill of materiel, and process constraint and rules) from high-level systems are received by IIASMP when actual data changes, and corrections are returned. Some ordinary interface technologies (e.g., files, web service, sockets, message, database, etc.) are adopted in IIASMP to enable this interface function.

Interfaces for horizontal integration (e.g., MES and SCADA): A manufacturing execution system is defined as an online integrated computerized system that contains the methods and tools used to accomplish production (Huang 2002). The basic functions of MES, such as quality control, material delivery, and WIP tracking, are furnished with

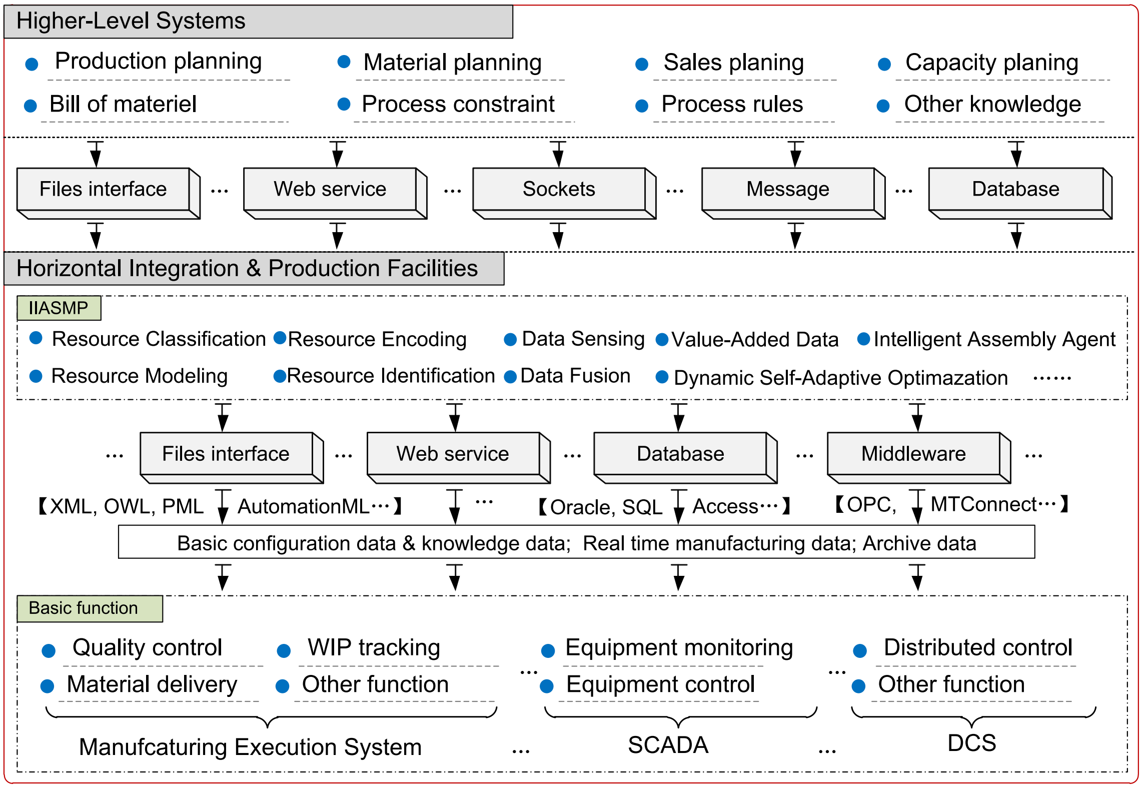

Fig. 13 Interface with different system levels

dedicated data collection systems (Kletti 2007). SCADA is also a system that operates with real-time signals to provide equipment control. The proposed IIASMP mainly focuses on the framework and key enabling technologies rather than the basic function of assembly system under the IoT environment. Some key enabling technologies (e.g., data collection) are actually used in some integrated computerized systems (e.g., MES, SCADA). Therefore, interfaces are necessary for horizontal integration. Three types of interfaces are involved in this part, namely, basic configuration data and knowledge, real-time manufacturing data, and archive data interfaces. Each interface is supported by some interface technology, such as various files (e.g., XML, PML, OWL, and AutomationML), web service, database, and middleware (e.g., OPC and MTConnect).

Interfaces with production facilities: The most important data that an integrated computerized system passes on to the facilities are set-point inputs, process value inputs, formulations and mixes, and programs (Kletti 2007). Therefore, interfaces with facilities, such as machines, machine groups, and production lines, are indispensable to the IIASMP. An IIASMP not only receives data (e.g., the counting signals, operating signals, resource status, measured values, and process data.) from the facilities but also sends instruction data. This task is performed by an intelligent assembly agent, which integrate some heterogeneous facilities, facilitate data exchange, and perform tasks.

Limitations, realizability, and expected benefits

After presenting the framework and key techniques of IIASMP, this section mainly discusses the limitations, realizability, and expected benefits of the proposed approaches : what kind of limitations and problems will be encountered, how to cope with these limitations and problems, how to make the proposed approach achievable, what benefits will be brought by this approach. All of the issues will be discussed as follows.

Limitations or problems

Manufacturing systems are complex and have various layers and entities can be heterogeneous. This part analyzes conceivable problems and limitations that should be expected, as well as how to overcome them to ensure interoperability. Several problems are discussed as follows.

1. Different assembly systems of mechanical products have different types of manufacturing resources. Therefore, the resource-encoding rules are not exactly the same as

that of the proposed encoding rules. Some research on the assembly system of typical mechanical products (e.g., car, engine, gearbox, axle, etc.) should be conducted. A multi-encoding library should be constructed to cope with this problem after conducting the research.

2. This paper constructs the resources data model on the basis of ontology, where some common semantic languages (e.g., XML, PML, and OWL) are used. However, these semantic languages cannot exactly support the semantic description of all the resource data. Therefore, a custom semantic language should be developed and applied.
3. The device driver is limitedly provided by IoT middleware. Although the IoT middleware (e.g. Kepserver) provides interoperability that allows automation control information to be leveraged throughout the organization, the IoT middleware cannot cover most heterogeneous devices. Therefore, HMI should be provided for data input. Moreover, custom drivers should be researched and used if possible.
4. The intelligent assembly agent is not completely smart. For example, enterprises cannot equip a double PLC for each assembly agent because the purchase cost of PLCs is high. The smart assembly agent cannot perform self-maintenance when the PLC fails. The intelligent assembly agent can adapt the operation environment if the knowledge library of the smart assembly agent is updated regularly.
5. Evolution based on data mining is hard to achieve. However, this research can achieve data mining to some extent, such as characterization, description, association, categorization, prediction, and clustering. The research on data mining for the assembly system of mechanical products is inadequate and incomprehensive. Therefore, data mining in assembly processes should be focused on.
6. The optimization model (algorithm) does not have intelligence features. The optimization model can only achieve data operation based on sensing data. Therefore, the determination of whether the optimization model is reasonable is important. The algorithm should be optimized regularly to cope with this issue.

Realizability

The overall infrastructure of the IoT-enabled intelligent assembly system is mainly supported by six key parts, include resource identification (manufacturing resource classification, encoding, and resource modeling), information interaction, multi-source data perception and sensing data fusion, value-added data, self-adaptive optimization, and smart assembly agent. The assembly system can achieve closed-loop control under the interactions of each part. The realizability of each part is described in the corresponding sections. The realizability of each part is generalized as follows.

1. Manufacturing resource classification and encoding are common issues that have been studied for a long time. This paper usually needs to consider the IoT-enabled resource features and perform relevant adjustments.
2. Ontology is used to facilitate data interaction, sharing, and reuse, is often captured in a semantic network, and is represented by a graph whose nodes are concepts or individual objects and whose arcs represent relationships or associations among the concepts (Lee et al. 2006). Therefore, the ontology-enabled resource model provides a systematic way to describe resource data and is linked to the concrete ability to write and store knowledge in an optimal manner. The most common systematic languages are XML, OWL, and PML, which have been widely used in the manufacturing field.
3. IoT middleware is a suitable technology for achieving heterogeneous data collection, transformation, and integration. Some countries and organizations have been focusing on the development of this technology. However, Kepserver is widely used in the industry. Drivers for open standards and most industry leading automation vendors are supported. More than 200 protocols can span most industry.
4. The collected data are described by systematic languages (e.g. XML, OWL, PML) and then compressed and transferred for data application on the basis of the data interaction standards provided by the Rockwell FTPC platform. Data compression, block storage, and block parsing are common methodologies in data processing.
5. Integrated data are mined for different applications after receiving and parsing the data block (e.g., equipment monitoring, tracking of the product, statistics and quality control, real-time material delivery, etc.). Each application applies different algorithms or models to achieve the objective of value-added data, which has been proven achievable. Subsequently, the mined data are transformed into visual information that can be directly understood by decision makers. The graphics device interface (GDI+) is used in this research to achieve this goal.
6. Multi-agent or agent issue, which has been explored and used for a long time, is a hot issue in the industry. In this context, the IoT-enabled assembly agent has the ability of comprehensive-sensing. The assembly agent becomes more and more intelligent, especially with the rapid development and implementation of vision-sensing technology. Vision sensor can complete many functions (e.g., detection, recognition, monitoring, etc.). Therefore, the control and management processor (e.g., PLC, indus-

try computer) can better understand the assembly environment and take corresponding action.

Expected benefits

The IoT aims to apply the Ethernet and Internet technologies in the industry to gather the manufacturing resources together based on the traditional control network (e.g. sensor networks, bus network, etc.). The IoT middleware is proven the important technology to achieve this objective. Enterprises need to deploy IoT middleware on system servers, and develop production management and control system based on IoT middleware. Therefore, the installation cost is relatively low. The assembly system of mechanical products can mainly benefit from the following aspects based on the comprehensive sensing data.

1. The system can further achieve data sharing between heterogeneous equipment to reduce production time and improve production efficiency. IoT middleware can address the "information isolated island" better to some degree.
2. The real-time consumption data of the assembly materials can improve the precision of material delivery to reduce cost caused by backlog of materials.
3. The quality prediction system could give satisfactory prediction accuracy based on the sensing data to improve the quality of production.
4. The assembly system can adapt some fluctuations to some extent based on the dynamic self-adaptive optimization approach.

Case study

A case study is conducted to show the current research achievement following the proposed concepts, framework, and key technologies of IIASMP in the preceding sections. This research is based on the IoT-enabled virtual simulation lab of a production system, supported by some automobile enterprises, national science foundations, and programs of China. Some of the key technologies have been used in the assembly shop floor for mechanical products (e.g. automobile, engine, gearbox, axle, clutch, etc.), and achieved good effects.

Figure 14 shows the IoT-enabled virtual simulation lab of a production system. It is mainly concerned with the scheduling, batching, data collection, process monitoring and control, dynamic self-adaptive optimization, and decision making for mechanical production systems. The lab is usually used for experimental teaching. The lab is also used for some related project verification and enterprise pre-acceptance tests. The lab could carry out the following experiments and project verifications.

1. Visual modeling and simulation of production systems.
2. Manufacturing process planning and simulation.
3. Planning and design of intelligent assembly system of mechanical products.
4. The human–computer interaction technology.
5. Production line balancing and optimization.
6. Logistical planning for production system.
7. Online optimization of manufacturing process.
8. Design, development, and validation of manufacturing process monitoring and control platform.
9. Development and validation of key technologies of IoT.
10. Robot programming, application, and simulation.
11. Electrical programming, control, and application.
12. Mechanical and electrical integration.

Figures 15, 16 and 17 show the current achievements of IIASMP. Figure 15 mainly shows the encoding and identification of resources and fusion. Figure 16 shows the IoT-enabled assembly agent as well as data sensing and processing. Figure 17 shows the applications and decision-making of IIASMP. The following core steps can be seen in Fig. 15: hardware configuration, data address mapping, address-object mapping, resource encoding, smart assembly resources, and data exchange. These core steps verify some proposed key technologies in the previous section. The six core steps are as follows.

Step 1: Hardware configuration. Some standard hardware configuration software and communication technologies are used to enable some heterogeneous devices to connect with each other.
Step 2: Data address mapping. Middleware is employed to configure the mapping relationship between device addresses and middleware items for object-oriented programming and other uses.
Step 3: Address-object mapping. Middleware items are added to the repository for some related component loading and initialization and to build the relationship between middleware items and production events and assembly resources.
Step 4: Resource encoding. Sensing data generally contain five class codes. Classes 1 and 2 codes are used for resource classification. These codes are related to the rest of the class codes, but not involved in the sensing data. By contrast, the other class codes are used for assembly resource identification and other uses. They are usually printed and involved in sensing data. For example, material barcode usually contains three parts, namely, the material code, supplier code, and serial code. These parts contain data length, start bit, and end bit properties.

Fig. 14 IoT-enabled virtual simulation lab of production system

Step 5: Personnel, machine, material, and other assembly resources are equipped with RFID tags, barcodes, sensors, visual devices, and so on, to make them and their condition identifiable and to achieve data physical sensing via information unit.
Step 6: Data exchange and display. First, data callback functions and services provided by middleware software are registered. Subsequently, data from devices via middleware server are collected, and uncertain sensing data are converted to meaningful data based on the mapping relationship among middleware items, production events, and assembly resources. Finally, production events are triggered, and corresponding functions are executed.

Bolt tightening workstation is a typical assembly agent. It is composed of several components, such as sensors, visual unit, robot, controller, and tightening machine. Figure 16 shows that the tightening process is divided into the following 14 steps based on the actual manufacturing activity:

Steps 1–3: The first three steps are about resource configuration, data address mapping, and address-object, which are introduced in the previous paragraph.
Step 4: Release of the pallets of the input buffer. The agent controller (control and management processor) controls the stopper (execution unit) to release a pallet into the assembly area if the manufacturing agent is idle and if the input buffer has pallets sensed by the photoelectric sensor (information unit).
Step 5: Release empty pallet. The agent prompts the stopper to release the empty pallet into the out-buffers if the photoelectric sensor sensed that the released pallet is empty or without WIP.

Step 6: Read RFID tag. Agent controller calls the RFID reader (information unit) to sense the data chain of WIP from the RFID tag (identifying unit).
Steps 7–8: Do watchdog check based on the data chain and check rules (knowledge library). Agent controller checks whether the WIP could meet the production requirements in the previous process.
Step 8: Release unqualified WIP. The agent controller releases the unqualified WIP into repair area if the WIP did not pass the watchdog check.
Step 9: Scan material code. Agent controller calls the scanning device to scan and parse material code (identifying unit) if WIP passed the watchdog check, then judges if the WIP type (knowledge library) matches the material type (knowledge library).
Step 10: Visual inspection. The material images captured by the vision device (information unit) are directly used to inspect and determine whether the values of quality detection are within the specifications (knowledge library).
Step 11: Material handling. The agent controller controls robot (execution unit) to grasp and handle a material based on machine vision if quality is within the specifications (knowledge library).
Step 12: Fix material. The agent controller calls the fixtures (execution unit) to fix the materials for assembly when the robot completed the material handling.
Step 13: Bolt tightening. The agent controller boots the tightening machine to achieve the process functions (e.g., bolt tightening and tightening results detection).
Step 14: Check quality values. The agent controller monitors the quality values captured by the torque and angle sensors (information unit) and determine whether the values of quality detection is within the specifications (knowledge library). The agent controller (control and management processor) controls the stopper (execution unit) to release a pallet into out-buffers if the values are qualified and the out-buffers are empty.

Figure 17 shows the applications and decision-making of IIASMP. The top of the figure illustrates the publishing of visual monitoring and information, each of which is drawn using defined graphic tools developed by the virtual simulation lab. Parts of the graphic tools are the basic elements

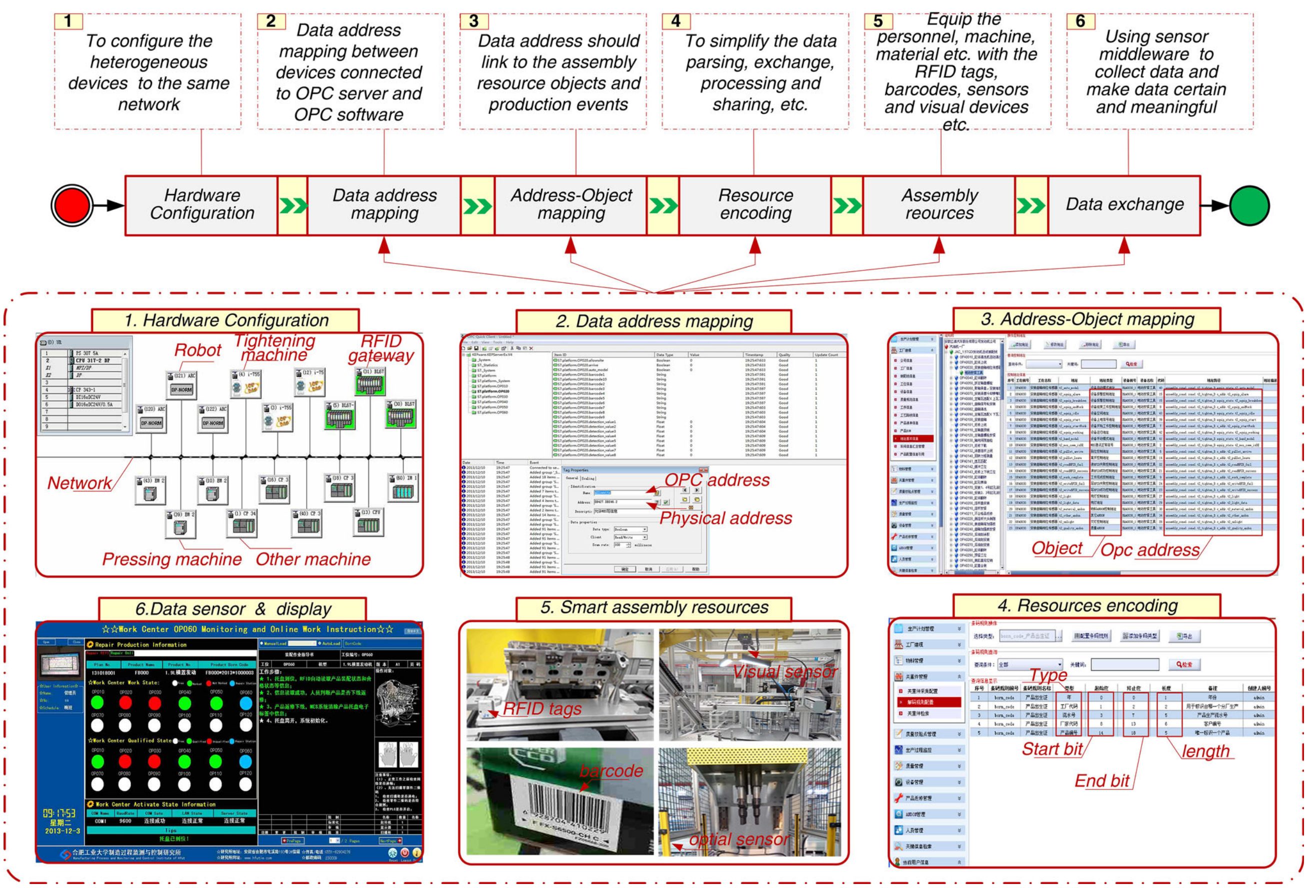

Fig. 15 Resources encoding and data perception and fusion

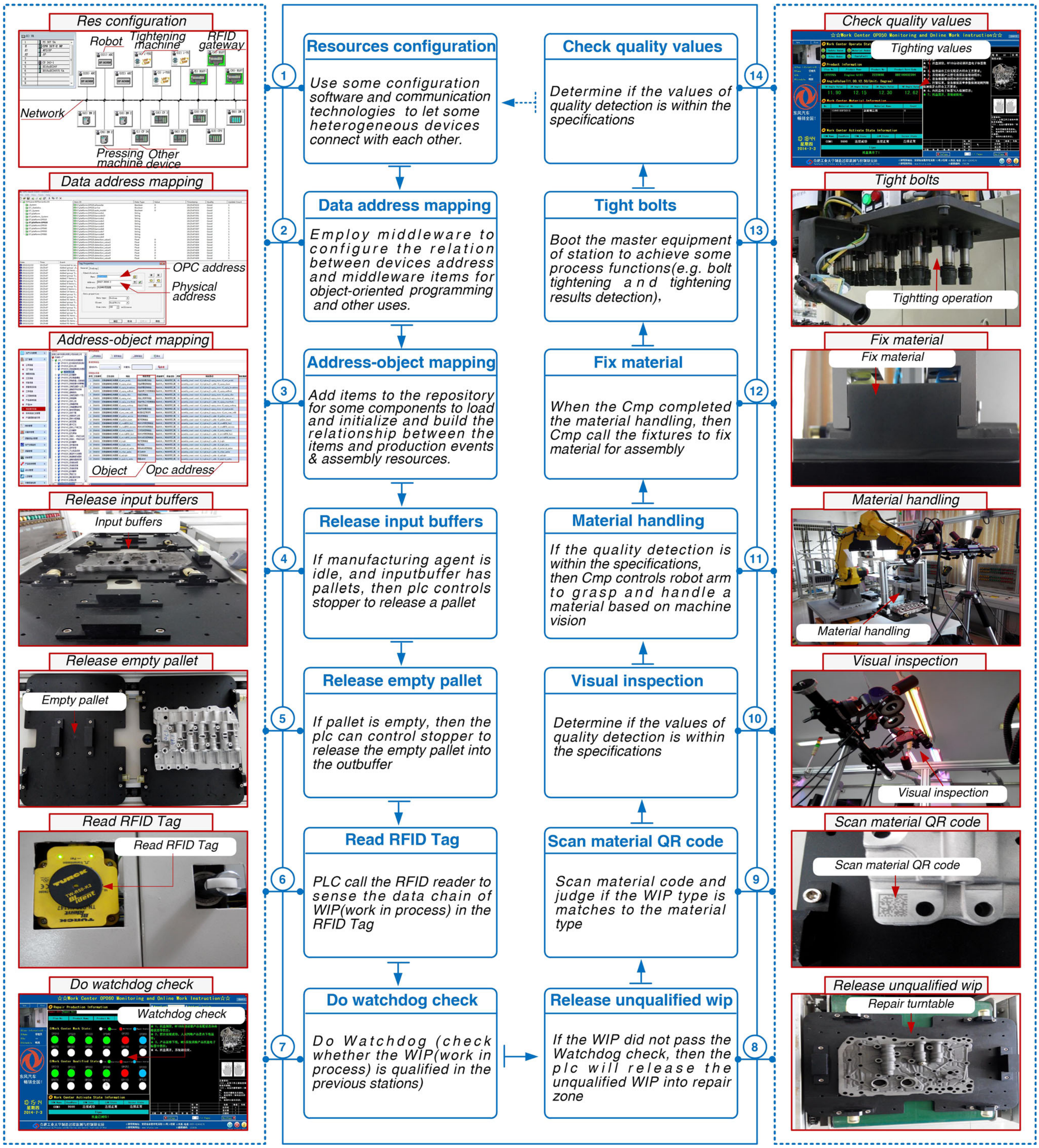

Fig. 16 Current research results for intelligent assembly agent

of visualization configuration, such as rectangle, ellipse, and straight-line, which are not related to the assembly resources. However, the other graphic tools (e.g., operator, material, RFID, equipment, Andon, resource's state, and other signals) are related to the assembly resources where every tool includes some properties, such as OPC items, production events, displayed colors, and alarm sound. The first three pictures show the overall, zone, and resource monitoring of IIASMP. The fourth picture displays the real-time production information of the shop floor. The bottom of the figure illustrates the enterprise applications based on value-added data, such as statistical process control (SPC), overall equipment

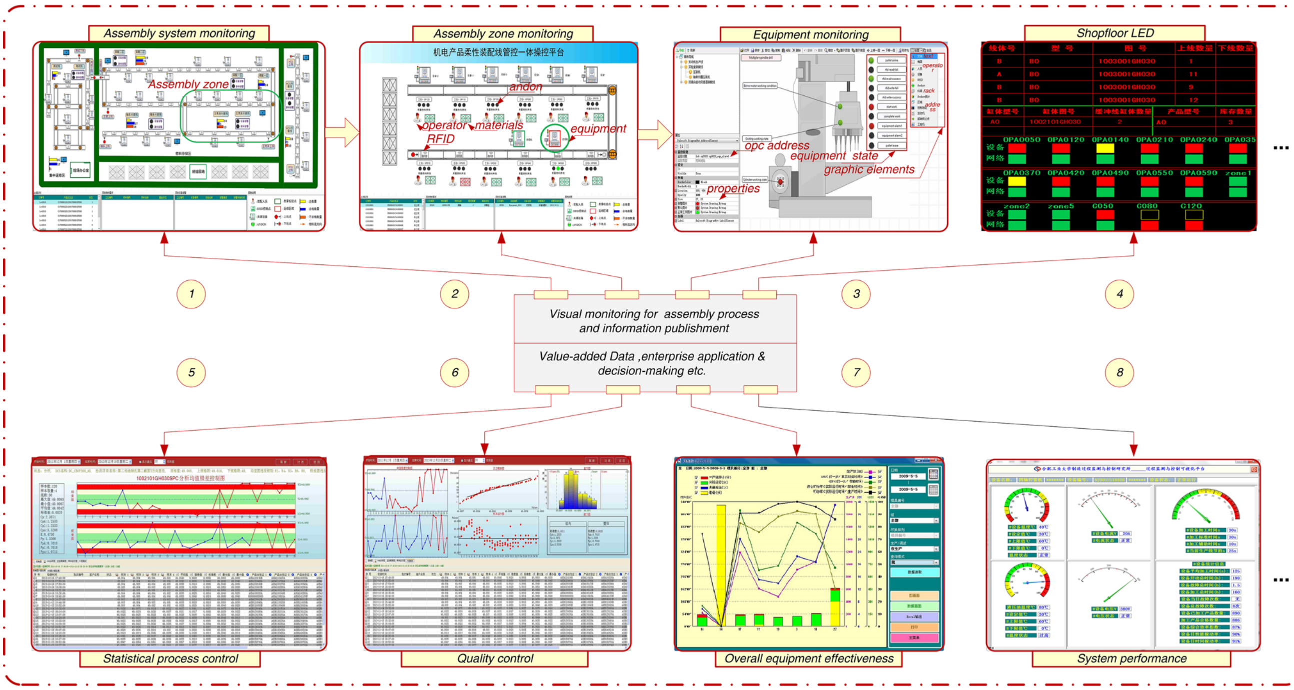

Fig. 17 Application and decision making of IIASMP

effectiveness (OEE), mean time between failures (MTBF), devices consumption energy, utilization rate, jobs per hour (JPH), and first time through (FTT). All of them support enterprise decision making and achieve stable production.

The "Internet of Things" is a generic term, but it has the following specific contextual meaning in this research: resources identification, sensing, communication, interaction, semantic middleware, and IoT-based application. However, some of the enabling technologies (e.g., different types of barcodes, active and passive RFID, sensing network, and information integration) have already been used in constructing the digital manufacturing system. In fact, the origin of this research is from a joint-school project carried out by the virtual simulation lab of production system based on previous research achievements and advanced manufacturing technology. Currently, some enabling technologies are adopted and used to increase the flexibility and automation of the assembly system for mechanical products.

Figures 15, 16 and 17 show the current achievements of IIASMP. The old production model with characteristics of mass production and assembly line lost its flexibility and even its scale advantage in the heterogeneous market. Currently,

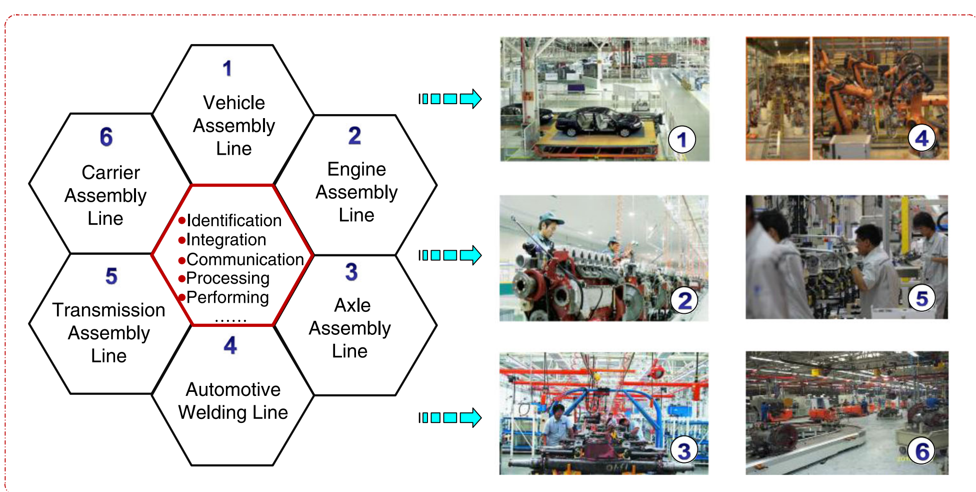

Fig. 18 Current application areas for IIASMP

automotive assembly systems are subject to many technological transformations because of their need to adjust to a continuously changing market. Manufacturers, in their effort to remain competitive, seek new technologies and equipment, which will allow their companies to increase their responsiveness to demand fluctuations and variability. Agile, modular, and autonomous assembly systems are considered as the most suitable solutions. Every process in the assembly plant has to become more flexible to increase the flexibility of the overall system (Michalos et al. 2010). Therefore, the proposed IIASMP will increase the flexibility of assembly for mechanical products based on IoT, which is part of the flexible or programmable automation. Currently, some of the proposed approaches have been used in some assembly of mechanical products, such as vehicle, engine assembly, axle assembly, automotive welding, transmission assembly, and carrier assembly lines. Figure 18 shows the current application areas of IIASMP. However, new technologies will be introduced into the manufacturing system to increase the flexibility of assembly for mechanical products with the development of IoT.

Conclusion

Recently, the rapid development of IoT technologies has created opportunities for developing an intelligent assembly system of mechanical products. An IIASMP and its key technologies are discussed and developed in this paper. The contributions of this paper could be summarized as follows:

1. The concept of IIASMP is proposed, which aims at improving the efficiency and intelligence of the assembly system to some extent.
2. An overall framework of the IIASMP is presented and discussed based on the advanced techniques (e.g. computer and information technologies, sensor network and RFID, etc.) and IIASMP concept, an overall framework of the IIASMP is presented and discussed.
3. Under the infrastructure of IIASMP, the key technologies are described, which support the resources encoding, data collection, analysis, and extraction, under the infrastructure of IIASMP to achieve decision optimization of the assembly process and the intelligent operation of the assembly system to some extent.

It is known the manufacturing process is composed of several stages, namely, resource identification, resource recognition and data collection, data transmission, data mining, and feedback control. Each of the stage is supported by the relevant key technologies proposed above. The proposed framework and key technologies of IIASMP provide a referenced framework and approaches to make the assembly system of mechanical products become more efficient and intelligent.

Some of the key technologies have been used in the assembly shop floor and achieved good effects, especially in the manufacturing execution system. However, some challenges, which will be focused on the future research works, still need to be overcome. The existing challenges are as follows.

1. The principal challenge is the completeness and comprehensiveness of wisdom repository. In other words, to the process of building a wisdom repository (e.g., optimization models, and algorithm) for multi-product to support the running of intelligent assembly system.
2. General interaction protocol. The process of standardizing the information interaction protocol for IoT-enabled intelligent assembly system is another future research direction.
3. New control strategies and management methods based on IoT, such as motion sensing, defection detection and judgment, online quality control, and online optimization.
4. With the development of IoT, new technologies and approaches will be introduced into the manufacturing system to increase the flexibility of assembly for mechanical products.

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