

# A Big Data Centric Integrated Framework and Typical System Configurations for Smart Factory

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**Abstract.** Personalized consumption demand and global challenges such as energy shortage and population aging require flexible, efficient, and green production paradigm. Smart factory aims to address these issues by coupling emerging information technologies and artificial intelligence with shop-floor resources to implement cyber-physical production system. In this paper, we propose a cloud based and big data centric framework for smart factory. The big data on cloud not only enables transparency to supervisory control but also coordinates self-organization process of manufacturing resources to achieve both high flexibility and efficiency. Moreover, we summarize eight typical system configurations according to three key parameters. These configurations can serve different purposes, facilitating system analysis and design.

**Keywords:** Smart factory · Smart production · Smart product · Industry 4.0 · Industrial internet

## 1 Introduction

For a long time, shop-floor manufacturing resources in terms of machines and conveyers have been carefully organized to build production lines which are efficient and low-cost for mass production. However, the traditional production line is rather rigid so that it will lead to a long system down time and an expensive cost to change for another product type. To cope with ever increasing personalized consumption demands on multi-type and small- or medium-lot customized products, many advanced manufacturing schemes such as flexible manufacturing system (FMS) or intelligent manufacturing system (IMS) have been proposed. The researches on FMS expect to allocate manufacturing resources to a family of product types with a kind of central computerized controller [1, 2]. By contrast, the multi-agent system (MAS) method, a representative IMS scheme, models resources as autonomous agents that rely on peer to peer negotiation to dynamically reconfigure for different product types [3, 4].

Today, emerging information technologies raise credible opportunities to implement smart production. With cloud computing [5], big data [6–8], wireless sensor network (WSN) [9], Internet of Things (IoT) [10], and mobile Internet [11] et al. applied in manufacturing environment, machines, tools, materials, products, employees, and information systems (e.g., ERP and MES) can be interconnected and communicate with each other.

This actually forms a manufacturing oriented cyber-physical system (CPS) [12, 13] or called cyber-physical production system (CPPS), which is the basis for smart factory termed by industry 4.0 initiative [14]. Compared with FMS and IMS, the smart production enabled by smart factory features high interconnection, mass data, and deep integration. Moreover, the product acts as a smart entity participating in the production process actively. Therefore, based on high bandwidth network and powerful cloud, smart production can implement high flexibility, high efficiency, and high transparency [15, 16].

In this paper, we propose a layered framework for smart factory to integrate shop-floor entities, cloud, client terminals, and people with industrial network and Internet. Big data and self-organization of smart shop-floor entities are two essential mechanisms to implement smart production. Big data enables transparency and coordinates self-origination process to achieve high efficiency. Self-organization makes reconfiguration process for multi-type products very flexible. To account for the diversity of shop-floor manufacturing resources, e.g., digital product memories (DPM) can be classified into storage, reference, autonomous or smart [17], and production execution can be alternative or hybrid, we propose an analysis model and identify three key parameters, according to which eight typical system configurations are recognized.

The article is organized as follows. In Sect. 2, we discuss the roles of cloud, big data, and self-organization in the smart production environment. In Sect. 3, the key parameters that affect reconfiguration ability, negotiation mechanism, and deadlock prevention are identified based on system analysis. In Sect. 4, eight typical configurations are constructed based on three key parameters, characteristics and application scenarios of which are further discussed. Finally, conclusions and future work are given in Sect. 5.

## 2 Integrated System Framework

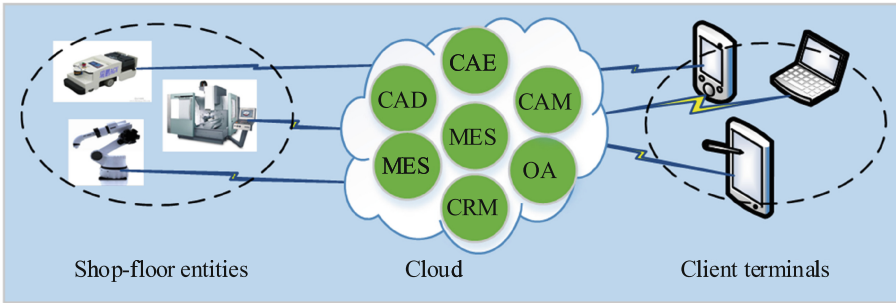
Smart factory focuses on vertical integration of various components inside a factory boundary. It is a kind of manufacturing oriented cyber-physical system, i.e., cyber-physical production system that features high flexibility, high efficiency and high transparency. In this section, we present an integrated system framework and discuss related issues.

### 2.1 Cloud Based Integration

Figure 1 depicts a framework to integrate shop-floor entities, servers, client terminals, and people with industrial network and Internet. Shop-floor entities mainly include machines (for processing, assembling, testing, and storing et al.), conveyers (such as conveyor belts, AGVs, and loading/unloading robotic arms), and intelligent products (being processed by the system). Servers are specific computers for hosting various information systems such as ERP, MES, and CAX (CAD/CAE/CAM) systems. Client terminals in the form of computers and smart mobile phones et al. are for human-system interaction. People mainly refer to employees that distribute among various sectors, e.g., production, operation and maintenance, design, purchasing, sale, finance, and planning.

However, non-employees such as suppliers, customers, and supervisors can also link to this network.

Traditionally, separate servers are used for different information systems. However, with cloud computing technology, a network of servers can be virtualized as a huge resource pool to support elastic computing and storage demand. Therefore, different information systems can be deployed onto the single cloud platform, and distributed shop-floor entities and client terminals can be connected to the same cloud as well. As a result, all the enterprise activities ranging from design and production to management and planning are integrated based on cloud.



**Fig. 1.** Cloud based integrated framework of smart factory.

## 2.2 Big Data Based Fusion

Both shop-floor entities and client terminals can act as data terminals to gather various kinds of data to cloud (outer race of Fig. 2). However, the simple migration of information systems from separate servers to the single cloud is not enough to create meaningful big data. Today's information systems are designed to cope with different requirements, e.g., CAD for product definition, MES for production process management, and ERP for resource management. As a result, they will probably use different formats to describe the same data object causing inconsistency to block information flow among different systems.

For big data to come true, smart factory should be constructed in a data centric way (inner race of Fig. 2). A unified data model including vocabulary, syntax, and semantics should be defined to maintain consistency, continuity, and integrity of mass data. Therefore, different information systems can operate on the same data object set. As software modules interact with each other through data objects, tight logic coupling can be released so that information processing software can be further modularized and miniaturized (middle race of Fig. 2). This facilitates software deployment and lower cost, e.g., software modules can be selected on demand. Recall that both big data and information processing software run on cloud, whereas shop-floor entities and client terminals are connected with cloud through industry network or Internet.

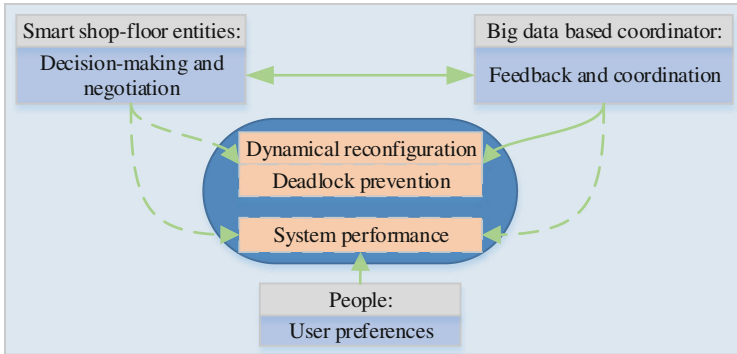


others. Through autonomous decision-making and negotiation, smart entities cooperate with each other to achieve system-wide goals, in a self-organized way, making the reconfiguration process very flexible.

## 2.4 Performance Optimization via System Evolution

Cloud and network are important infrastructures, while big data and self-organization are essential mechanisms of a smart factory. Smart entities and big data analytics based coordinator construct a kind of distributed decision-making system. We rely on self-organization of smart entities to implement high flexibility. Big data, on the other hand, helps coordinate global efforts such as deadlock prevention and performance optimization.

When design decision-making and negotiation mechanisms of smart entities and customize behavior of the coordinator, dynamical reconfiguration, deadlock prevention, and performance optimization are three key goals. Deadlocks occur due to the fact that multiple products will compete for limited resources. System performance has a lot of indicators such as efficiency, utilization rate of machines, and load balance. Dynamical reconfiguration and deadlock prevention are fundamental requirements while system performance is desired to improve progressively with increasing experience and data. Moreover, user preferences can also affect system evolution, but they are generally preset and static. The related components and their relationship is shown in Fig. 4.



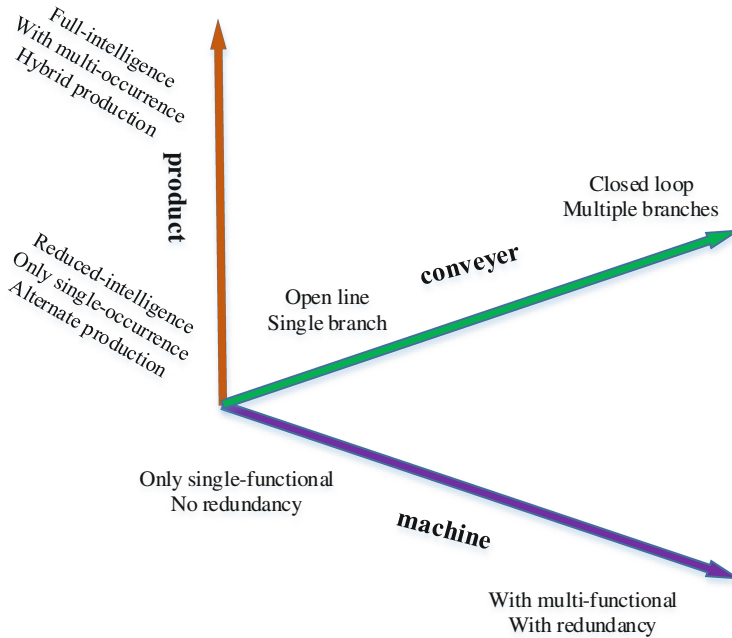
**Fig. 4.** Main participants and key indicators in smart production system.

## 3 System Analysis of Shop-floor Entities

As mentioned above, machines, conveyers, and products are main kinds of shop-floor entities. In this section, we define seven system parameters to describe system characteristics, three of which are further recognized as the key parameters.

### 3.1 System Analysis

Machines, conveyers, and products have some special characteristics which form a design space for constructing various production systems, as shown in Fig. 5.



**Fig. 5.** System configuration space in terms of machines, conveyers, and products.

For machines, one that has multiple sub functions is defined as multi-functional machine, whereas one that has only one function is defined as single-functional machine. If all the machines have different sub functions from each other, no functional redundancy exists, whereas two or more machines having the same sub functions introduces functional redundancy.

For conveyers, the resultant conveying route is either open or closed. Moreover, a route may have branches. While single open line is the simplest production line, multiple open lines can intersect with each other to form a complex route. Similarly, single loop is simple and applicable, whereas multiple loops can be linked together to build complex circular routes.

For products, the full-intelligence product can make decisions and negotiate with others by itself, whereas the reduced-intelligence product may do not have abilities of computing and communication, e.g., the product only attached with a RFID tag. Moreover, each product type specifies a sequence of operations. Therefore, in an operation sequence, if only one operation belongs to an operation type one defines the operation type as the single-occurrence (operation) type. If two or more operations belong to the same operation type, one defines the operation type as the multi-occurrence (operation) type.

The smart factory is for production of multiple types of products. However, this can be classified into alternate production (one type of products is processed after another) and hybrid production (multiple types of products are processed simultaneously).

The aforementioned characteristics are summarized as system parameters (Table 1) and each parameter, like Boolean variable, has only two mutually exclusive values. As the number of parameters is seven and each has two possible values, a variety of one hundred and twenty-eight different system configurations can be determined.

**Table 1.** System parameters and their allowed values.

		Parameters						
		1	2	3	4	5	6	7
Value	A	Only single-functional	No redundancy	Open line	Single branch	Reduced-intelligence	Only single-occurrence	Alternate production
	B	With multi-functional	With redundancy	Closed loop	Multiple branches	Full-intelligence	With multi-occurrence	Hybrid production

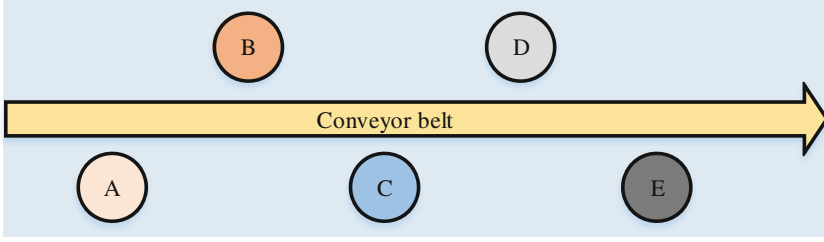
### 3.2 Key Parameters

For parameters 1, 2, 4, and 6, the value B addresses more general and practical situations than the value A does. For example, even one multi-functional machine can change parameter 1 from value A to value B. The system that allows functional redundancy is easier to deploy and the redundancy helps to guarantee robustness, e.g., in case of machine failure. The conveying system with multiple branches can extend to large space and adapt to complex topology. The multi-occurrence operation types are sometimes not avoidable considering the resource constraints and repeated operations. Therefore, when developing algorithms, the value for parameters 1, 2, 4, and 6 is assumed to be B; the developed algorithms are compatible with value A, as the value A addresses simple situations.

For parameter 3, the open lines are used widely in the traditional production lines. However, the open line will limit system's reconfiguration ability. As shown in Fig. 6, five machines for operation types A, B, C, D, and E are deployed along the unidirectional conveyor belt. Any product types that require operation sequences like [A, B, C], [B, C, D], and [A, C, E] can be processed as the fixed order from A to E is kept, whereas the operation sequences like [A, C, B] or [E, D, C] cannot be supported as the conveyor belt cannot route the products back from C to B or from E to D. By contrast, the closed loop conveying system like circular conveyor belt or bidirectional AGV can route products between any two machines. Therefore, this system parameter affects system reconfiguration ability, i.e., value B (closed-loop) can support complex reconfiguration whereas value A (open line) cannot.

For parameter 5, the product with full intelligence can participate in negotiation process as an active agent, whereas the product with reduced intelligence is passive and should rely on other components, i.e., machine or conveyer, to help it. Therefore, this parameter affects negotiation mechanism and negotiation process.

For parameter 7, the hybrid production is more complex than the alternate production. The hybrid production makes production process highly dynamical that deadlocks will occur unexpectedly. Therefore, the hybrid production needs more powerful



**Fig. 6.** Production system with open-line conveyor belt.

deadlock prevention strategy than the alternate production does. In a word, this parameter relates to deadlock prevention strategy.

In summary, the parameters 3, 5, and 7 are recognized as the key parameters. They respectively affect reconfiguration ability, negotiation mechanism, and deadlock prevention strategy, i.e., value A and B of these parameters require different strategies. As to parameters 1, 2, 4, and 6, the value B covers the application range of value A, so they are not treated as key parameters and only value B is considered during design.

## 4 Typical Configurations and Their Application

The three key parameters can be used to determine eight typical system configurations. Based on parameter 3, the eight configurations are divided into two groups. We formulate each configuration and discuss their distinct characteristics in this section.

### 4.1 Typical Configurations of Closed-loop Production System

Table 2 summarizes four typical configurations featuring closed-loop production system. The value of parameter 3 is B (closed loop) for these configurations, but the value combination of parameters 5 and 7 is different in each configuration.

*Alternative Production VS Hybrid Production.* As a general rule, efficiency increases with batch size. However, the alternative production is more sensitive to batch size than hybrid production, as illustrated in Fig. 7. This is because alternative production requires one type of products to be processed after another leading to system overhead in the case of product type switch. Hybrid production does not suffer this kind of overhead, as it can accommodate multi-type products simultaneously. As a result, the hybrid production suits for small-lot production whereas the alternative production is more efficient for medium or mass production.

*Full Intelligence VS Reduced Intelligence for Hybrid Production.* Full intelligence product can carry and maintain its own data/state, and it can make decisions for itself. Therefore, full intelligence product is quite suitable to be used with hybrid production to maximize system performance. By contrast, reduced intelligence product will lower agility and efficiency when used with hybrid production, although it is cheaper. This is

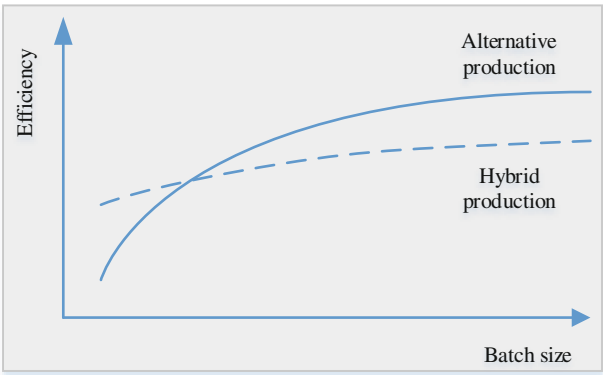


**Table 2.** Typical configurations of closed-loop production system.

Configurat ion	Value for parameters						
	1	2	3	4	5	6	7
1	A /B	A /B	B (Closed loop)	A /B	A (Reduced- intelligence)	A /B	A (Alternate production)
2	A /B	A /B	B (Closed loop)	A /B	B (Full- intelligence)	A /B	A (Alternate production)
3	A /B	A /B	B (Closed loop)	A /B	B (Full- intelligence)	A /B	B (Hybrid production)
4	A /B	A /B	B (Closed loop)	A /B	A (Reduced- intelligence)	A /B	B (Hybrid production)

because reduced intelligence product needs to set up data structures for new types of products frequently in small-lot hybrid production.

*Full Intelligence VS Reduced Intelligence for Alternative Production.* Reduced intelligence product will not cause obvious performance loss and can save cost when it is used with medium or mass alternative production, as product type switch is not frequent in the case of large volume.



**Fig. 7.** Efficiency versus batch size for alternative and hybrid production.

In summary, the configuration 1 is quite suitable for medium or mass production, while the configuration 3 suits well for small-lot production. The configuration 2 can achieve equal efficiency as (or a little more than) configuration 1 but with much more cost. The configuration 4 cannot achieve equal efficiency as configuration 3 although it can save cost. These configurations enable users to balance between efficiency and cost based on batch size when designing a smart factory.

## 4.2 Typical Configurations of Open-line Production System

Table 3 summarizes four typical configurations of open-line production system, where the value of parameter 3 is A (open line). Recall that the open line leads to very limited reconfiguration ability. The alternate production is possible as indicated in configurations 5 and 6, as long as the operation sequence is in accordance with the machine order. These two configurations suit for medium or mass production and the configuration 5 is cheaper than configuration 6. As to hybrid production, it is quite difficult to ensure the processing sequence of machines because of deadlock prevention, so configurations 7 and 8 are nearly not applicable.

**Table 3.** Typical configurations of open-line production system.

Configurat ion	Value for parameters						
	1	2	3	4	5	6	7
5	A /B	A /B	A (Open line)	A /B	A (Reduced- intelligence)	A /B	A (Alternate production)
6	A /B	A /B	A (Open line)	A /B	B (Full- intelligence)	A /B	A (Alternate production)
7	A /B	A /B	A (Open line)	A /B	B (Full- intelligence)	A /B	B (Hybrid production)
8	A /B	A /B	A (Open line)	A /B	A (Reduced- intelligence)	A /B	B (Hybrid production)

## 4.3 Algorithm Design for Typical Configurations

We have developed algorithms for configuration 2, and we find that negotiation process and deadlock prevention do not interrupt each other [18]. Therefore, if we could have developed algorithms for configuration 4, the resultant algorithms of configurations 2 and 4 can be used with configurations 1 and 3. Suppose that the negotiation mechanisms for reduced- and full-intelligence products are N1 and N2 respectively, and the deadlock prevention strategies for alternate and hybrid production are P1 and P2 respectively. Then the combination of N1 and P1 can be used to configuration 1, and the combination of N2 and P2 can be used to configuration 3. These strategies can also be used to configurations 5 to 8. However, special measures should be considered to account for the limited reconfiguration ability of open lines.

## 5 Conclusions and Future Work

By introducing cloud computing, big data, and artificial intelligence et al. into manufacturing environment, smart production is promising to achieve high flexibility, efficiency, and transparency. On one hand, smart shop-floor entities interact with each other to implement self-organization based dynamical reconfiguration. On the other hand, big

data enables transparency for management and maintenance and coordinates system-wide goals such as deadlock prevention and performance optimization. The variety of physical shop-floor resources exist in the manufacturing environment, where machines, conveyers, and products are main participants. Many parameters relate to these resources and some of them play important roles in system design and analysis. The conveying route, product intelligence, production model are three key parameters to affect reconfiguration ability, negotiation mechanisms for dynamical reconfiguration, and strategies for deadlock prevention respectively. Based on these key parameters, we identify eight typical configurations, suitable for a range of applications. In the future, algorithms and practical experimental prototypes will be designed, implemented, and verified.

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