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Design of a Smart Manufacturing System With the Application of Multi-Access Edge Computing and Blockchain Technology

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ABSTRACT Smart manufacturing is the core of the modern production and manufacturing industry as it moves towards digitalization. The successful implementation of smart manufacturing needs the support of information technology, data technology, and operational technology, among which edge computing, blockchain technology and artificial intelligence can play significant roles facilitating the development of smart manufacturing. In this research, a smart manufacturing system is proposed considering the integration of edge computing and blockchain technology. The introduction of edge computing can balance the computational workload and provide a more timely response for terminal devices. Blockchain technology can be utilized to promote both the device-level data transmission and the manufacturing service transaction. Moreover, regarding the computational task assignment in smart manufacturing systems, a mathematical model is proposed, and further solved using a swarm intelligence-based approach. Numerical experiments show that the introduction of the edge computing mechanism in smart manufacturing can significantly improve the processing time, especially with a large number of tasks.

INDEX TERMS Blockchain technology, edge computing, smart manufacturing, swarm intelligence.

I. INTRODUCTION

The evolution of industrialization has changed from automation to digitalization. Ever since the introduction of Industry 4.0 in Germany, various similar concepts or projects have been initiated in different countries or regions, such as the Industrial Internet from the US, Made in China 2025, Industry 4.1J from Japan, and Manufacturing Industry Innovation 3.0 from South Korea. Two intrinsic features of digitalization are the identification and connection of entities. On the one hand, the concept of internet of things (IoT) was initially introduced to manage the identification issue, which further derives the industrial internet of things (IIoT) with industrial specialization. On the other hand, the cyber-physical system (CPS) is introduced to solve the connection among various physical entities.

Smart manufacturing is the core of the modern production and manufacturing industry in regard to digitalization, which is also the foundation of the smart factory [1]. In the smart manufacturing process, massive terminal devices and facilities are digitalized and connected through information technologies (IT), such as radio frequency identification (RFID), WiFi, ZigBee, and 5G [2]. The interaction and interoperation among these devices create huge data stream continuously, which contains multifarious data processing requirements, e.g, large data volume, unstructured data type, and low time-delay. In order to streamline and expedite the data processing, data technologies (DT) are introduced, such as big

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data analytics (BDA), industrial cloud computing (ICC), and artificial intelligence (AI). Moreover, the incorporation of detailed control of machines into the data computation by the server is achieved using operational technologies (OT), such as the supervisory control and data acquisition (SCADA) system, distributed control system (DCS), and programmable logic controllers (PLC). In addition to the inner operation of smart manufacturing, the manufacturing process or the assembly line capability can be further digitalized as cloud manufacturing services

The integration of IT, DT, and OT underpins the development of smart manufacturing. However, the ever-increasing connected devices and facilities lead to high data processing requirements, and challenge the application of existing technologies. In order to alleviate this problem, multi-access edge computing (MEC) technology, derived from 5G technology, becomes a promising solution, and has the capability to facilitate the data processing between IIoT and ICC, and can also support the interaction and interoperability between IIoT devices [3]. Another problem beyond the technical application of smart manufacturing is the trustworthiness of the data transmission at the device level and the business transaction in the corporate level. Blockchain technology is the most favorable solution to solve this trust problem, which can strengthen the data transmission and business transaction using a distributed control mechanism [4].

Therefore, in this research, we investigate and analyze the potential issues of applying MEC and blockchain technology into smart manufacturing. A conceptual framework design for a smart manufacturing system is proposed, integrating both the MEC and blockchain technology. Moreover, with the application of MEC, the architecture of smart manufacturing is changed from centralized management to a distributed form, which leads to a task assignment problem from terminal devices [5] and the corresponding computing resource allocation problem among the edge servers [6]. Thus, we further introduce an optimization model to formulate the task assignment and resource allocation in the proposed smart manufacturing system. After that, we design a swarm intelligence-based approach to solve the mathematical model. Numerical experiments show that the designed algorithm can find near optimal solutions within a reasonable time, and the introduction of MEC to smart manufacturing can significantly improve the system performance.

The remainder of this paper is organized as follows. Section II briefly reviews the industrial evolution and recent emerging technologies. Section III introduces a conceptual framework for smart manufacturing systems considering the application of edge computing and blockchain technology. In section IV, a resource control mechanism concerning the task assignment from terminal devices is introduced. Section V introduces a swarm intelligence-based approach for solving the optimization model. In section VI, numerical experiments are conducted to examine and validate the performance of the proposed model and the effects of the proposed algorithm. Finally, some conclusions are drawn in section VII.

II. RELATED WORK

A. IoT, IIoT, INDUSTRY 4.0, AND CPS

The development of the IoT is the fundamental support for any digitalization. On the one hand, the application of IoT covers various aspects, such as smart cities, intelligent transportation, traffic monitoring, and wearable healthcare devices, while the IIoT covers the domain of machine-to-machine communication and interaction, which paves the way towards the digitalization of manufacturing processes, thereby enabling efficient production [7]. On the other hand, the CPS addresses the connection and interaction between the physical world and its digital counterpart, thus improving the production performance by visualizing and optimizing the manufacturing processes [8]. The concept of Industry 4.0 arises when the IIoT paradigm encounters the CPS, which is the most universally adopted solution to address the use of internet communication technologies (ICT) to improve the production efficiency by means of smart manufacturing in smart factories.

As shown in Figure1, Sisinni *et al.* [9] adopted a Venn diagram to illustrate the intersections of IoT, IIoT, CPS, and Industry 4.0. Yang *et al.* [10] identified the key issues and potential applications of the IoT in manufacturing area, and concluded that the IoT envisioned the seamless interconnection of the physical world and cyberspace and their pervasive presence. Apart from that, Wan *et al.* [6] introduced a cyber-physical production system (CPPS) that enabled efficient data transmission with intelligent network management tools, and reliable communication technology, which were the typical features of CPPS information interaction.

B. EDGE COMPUTING

The successful operation of a smart factory requires ultralow communication latency and a reliable working environment to achieve precise control over smart manufacturing processes. Aiming for that, the emerging MEC technology can satisfy these requirements. The European Telecommunications Standards Institute (ETSI) showed that MEC can provide cloud computing capabilities and an IT service environment at the edge of the network, despite the access technologies [11].

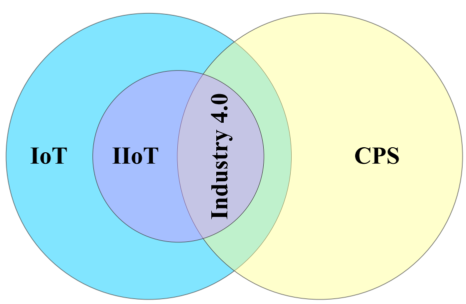

FIGURE 1. IoT, CPS, IIoT, and Industry 4.0 in Venn diagram [9].

Towards the application of MEC technology in IoT applications, Chen *et al.* [12] designed a multi-microcontroller structure as the edge gateway for the industrial internet, which combines the field programmable gate array-based hardware bridge and multiple scalable microcontrollers. Li *et al.* [13] proposed an adaptive transmission architecture with the support of global centralized software and defined network and edge computing for IIoT. Moreover, Yu *et al.* [14] surveyed the performance of edge computing architecture for IoT applications, like smart city, smart grid, and smart transportation. Porambage *et al.* [15] provided an overview on the exploitation of MEC technology for the realization of IoT applications and their synergies as well.

C. BLOCKCHAIN TECHNOLOGY

Blockchain technology can be viewed as a novel decentralized architecture and distributed computing paradigm, which stores data with encrypted chained blocks, and manipulates data with self-executed program scripts [16]. Yuan and Wang [17] summarized the key features of blockchain technology as decentralization, trust, security, chronological data, collective maintenance and programmability. It is acknowledged that three types of blockchain exist, i.e., public blockchain, consortium blockchain, and private blockchain, with different application background. Public blockchain is known as the foundation of various digital currencies. A promising application of the consortium blockchain is to ally multiple stakeholder entities and conduct business or service trading. For example, Li *et al.* [18] proposed an energy trading system using the consortium blockchain technology. Min [19] discussed the ways to leverage blockchain technology to enhance supply chain resilience in terms of the increased risks and uncertainty.

In addition to business trading, blockchain technology can also be adopted to facilitate IoT applications, which can be regarded as the implementation of the private blockchain. For instance, Yang *et al.* [20] designed IoT-oriented data exchange prototype system using Hyperledger Fabric in order to solve the issue of automatic maintenance of a tamper-resistant, reliable and distributed management system. Caramés and Lamas [21] conducted a review on blockchain application for the IoT and identified the challenges and optimization issues related to the deployment of a blockchain based IoT application. Moreover, Scriber [22] designed a framework for determining blockchain applicability through an analysis of more than twenty blockchain implementation projects.

Although there is some research related to applying edge computing for smart manufacturing, the incorporation of blockchain technology for data captured by production IoT devices has not been fully investigated. In addition, the issue of task allocation for multi-access edge computing needs to be addressed.

III. SYSTEM ARCHITECTURE

The incorporation of edge computing and blockchain technology can substantially facilitate data processing and data transaction in smart manufacturing systems, which are elaborated in the following subsections.

A. EDGE COMPUTING-BASED PROTOTYPE SYSTEM

The edge computing-based smart manufacturing system can be categorized as a three-tier system architecture, as shown in Figure 2. The first tier is composed of various heterogeneous terminal devices in terms of different kinds of sensors, actuators, machines, robots and so on, which constitute the

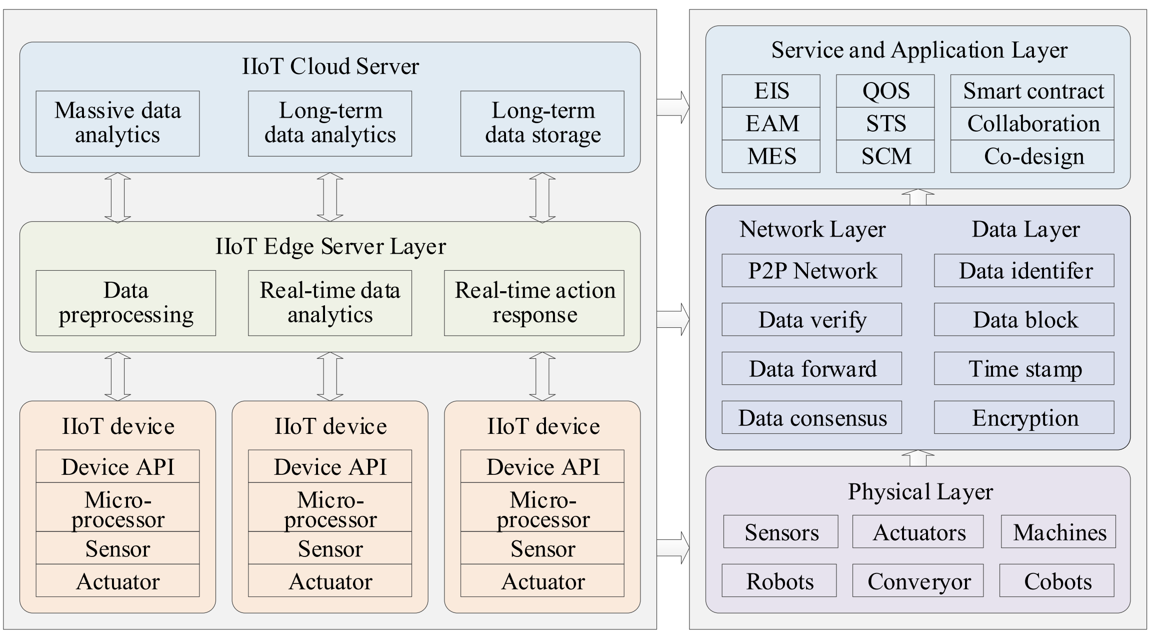

FIGURE 2. Edge computing-based smart manufacturing system architecture.

major component of the physical layer. The second tier is the deployment of multiple edge servers, which can either process the computational tasks from terminal devices, or forward these tasks to the third tier, i.e., the industrial cloud server. In contrast to the huge amount of storage and processing resources of the industrial cloud, edge servers have only limited capacity and resources to provide computational services. Therefore, as shown in Fig. 2, a cloud server commonly processes the tasks requiring massive and long-term data support, such as product design, customer analysis, and quality management. The data processing in IIoT cloud server is the foundation for various enterprise-level applications, like enterprise information system (EIS), enterprise asset management (EAM), service transaction system (STS), supply chain management (SCM), and so on. Comparatively, edge servers are more in charge of shop floor and machine level tasks featured with low-latency or nearly real-time management, e.g., the fine-tuning of control parameters for machines and assembly lines, and the adjustment of working environmental factors. The data transmission among IIoT devices, IIoT edge servers, and IIoT cloud server involves a number of functional requirements, such as data verification, data identifier, data encryption, etc., which paves the way for blockchain application.

The introduction of edge computing in smart manufacturing is much more than the complementary resources to cloud computing. It is necessary for the development of smart manufacturing due to its inherent easy connectivity and high scalability. The successful operation of edge computing relies on virtualization technologies, including virtual machines and virtual containers, which allows the parallel processing of multiple independent tasks simultaneously. The major difference between the virtual machine and virtual container lies in the isolation level and implementation mechanism, where the virtual machine involves a heavy-weight implementation requiring a full virtualized hardware, and the virtual container is light-weight implementation, in which all virtual instances share a single operating system kernel. Both the virtual machine and the virtual container technologies are incorporated to improve the resource utilization of edge servers. Moreover, because of the limited resources and capacities, it is of great necessity to assign the incoming tasks and allocate available resources in an optimal manner, as addressed in the following sections.

B. BLOCKCHAIN TECHNOLOGY-BASED DATA AND SERVICE VALIDATION

The application of blockchain technology in smart manufacturing makes a two-fold contribution. On the one hand, the introduction of edge servers and IIoT changes the manufacturing paradigm from a cloud-centered mode to a distributed system architecture. Under these circumstances, blockchain technology can be used to strengthen the data integrity and reduce the data transmission risks by enabling the identification, sharing and validation of key relevant data in a distributed manner. Specifically, blockchain technology, which can be used to identify the origin and destination of a specific data flow, examines and validates the completeness of the data package, and guarantees the integrity of responsive command data.

In order to track modifications and avoid faulty operation, all data transactions have to be signed and time-stamped on the blockchain, which can be implemented through the hash coding of the previous timestamp so as to maintain the order of data transaction and avoid the insertion of fake transactional data in a linked chain. Apart from the data validation mechanism, the consensus mechanism is another key for which the proper functioning of a blockchain determines the conditions as to whether a validated block can be added to the blockchain or not.

On the other hand, the digitalization of the smart manufacturing advocates the virtualization of manufacturing process, which leads to cloud manufacturing services. Blockchain technology can be used to facilitate service validation and transaction. As shown in Figure 3, the representation of manufacturing service involves two fields, i.e., meta-data and content, which provides a unique service identifier and a detailed function and process description respectively. Once a manufacturing service is well abstracted and characterized, a service block is created. Then the created service is broadcasted in the distributed manufacturing service network, which is further validated and approved by the majority of the network entities. Finally, the validated service is added to the service blockchain.

The transactional blockchain follows a similar pattern as the service blockchain. Once a certain manufacturing service is queried and purchased, a service transactional block will be created. Such a transaction block will also be broadcast in the same manufacturing service network and, further, be validated by other peer-to-peer entities. After that, this transaction block is added to the transaction blockchain. The above operational procedures of the transaction blockchain constitute smart contracts among multiple interactive business partners, of which the inner protocols can facilitate, verify, and enforce the performance or negotiation of a contract.

IV. COMPUTATIONAL TASK ASSIGNMENT

The edge computing-based smart manufacturing system is of high scalability, which suits expansion potentiality and data process requirements of massive IIoT devices [6]. As illustrated in Figure 4, the process of data transmission and analysis in this smart manufacturing system can be regarded as computational tasks, which need to be assigned and processed in the edge server or cloud, and the objective is to find the proper task assignment scheme so as to minimize the average processing time for the incoming tasks. In order to model this task assignment problem, it is assumed that the proposed smart manufacturing system consists of N terminal devices, E edge server nodes, and one industrial cloud server. During the manufacturing process, the terminal devices continue to request heterogeneous computational tasks, which are handled by either the edge server or the cloud server.

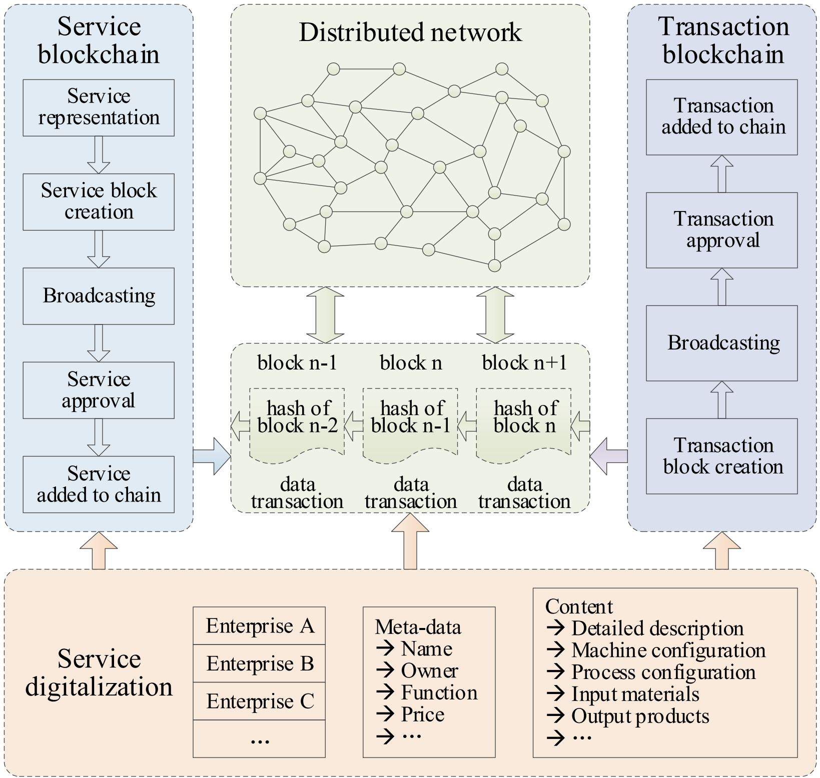

FIGURE 3. Blockchain-based manufacturing service transaction.

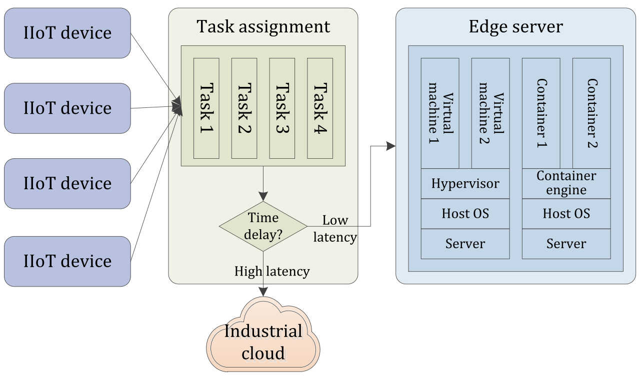

FIGURE 4. Computational task assignment in smart manufacturing.

Commonly, two popular technologies underpinning the application of edge computing are virtual machine technology and container technology, which possesses its own feature and fits different application scenarios. However, in this research, we treat them equally as the incoming computational tasks are homogeneous and abstract. The industrial cloud server has sufficient computational resources to process all types of tasks, whereas an edge server has limited computational resources allocated to process different tasks.

Let T be the set of tasks requested by all terminal devices, and each task $t \in T$ contains a certain amount of data and a specified maximum time delay as $t \triangleq < l_t, v_t, d_t >$, in which the unit of task length l_t is MI (million instructions), the unit of data volume v_t is byte, and the unit of time delay d_t is second.

The processing time for task t in edge server $e \in E$ involves two components, i.e., the computation time $\mu^e_{t,com}$ and the data transmission time $\mu^e_{t,data}$, which is expressed as follows.

$$\lambda^e_t = \mu^e_{t,com} + \mu^e_{t,data} \tag{1}$$

Specifically, the computation time of task t in edge server e is calculated as

$$\mu^e_{t,com} = l_t / \sum_{p=1}^{P^t_{max}} r^e_{t,p} \tag{2}$$

where $r^e_{t,p}$ represents the allocated computational resources by edge server node e for task t during the period p, P^t_{max} denotes the maximum number of period that the task can maintain, and l_t represents the length of task t as mentioned previously. To satisfy the delay constraint, P^t_{max} can be calculated as

$$P^t_{max} = \lfloor d_t / \rho_e \rfloor \tag{3}$$

where ρ_e is a time unit constant for edge server node e, which is expressed as the time length of a processing period.

To ensure that the task is completed on time, the task must be allocated with more resources than it needs, as

$$l_t \leq \sum_{p=1}^{P^t} r^e_{t,p} \tag{4}$$

where P^t is the actual number of periods consumed by task t.

The data transmission time between terminal device n and the edge server node e is calculated as

$$\mu_{t,data}^{e} = v_t / w_n^e \tag{5}$$

where w_n^e represents the radio bandwidth allocated by edge server node e, of which the unit is MBPS (million bytes per second).

Moreover, the allocated computational resource to tasks cannot exceed the total resources of the edge server, as

$$\sum\nolimits_{t\in T_p^e} r_{t,p}^{e} \leq R^e \tag{6}$$

where R^e denotes the available resource of edge server node e, T_p^e represents the task set running in the edge server node e during the period p.

If a task needs to be processed in cloud server, the *corresponding* processing time can be calculated as

$$\lambda_t^c = \mu_{t,com}^{c} + \mu_{t,data}^{e} + \mu_{t,data}^{e,c} \tag{7}$$

in which $\mu_{t,com}^{c}$ is the computational time, $\mu_{t,data}^{e}$ is the data transmission time between terminal device n and its corresponding edge server, and $\mu_{t,data}^{e,c}$ is the data transmission time from edge server e to cloud server.

The time delay constraint for each task is assumed to be a hard constraint, which cannot be violated when processing in either the edge server or the cloud server as

$$x_t^e\lambda_t^e + x_t^c\lambda_t^c \leq d_t \tag{8}$$

$$x_t^c + x_t^e = 1 \tag{9}$$

where x_t^e and x_t^c are binary variables to indicate whether task t is running in edge server node e or the cloud c, respectively.

The complete model is presented as follows, with which the objective is to minimize the average processing time for all tasks.

$$\min \sum\nolimits_{t\in T} \left(x_t^e\lambda_t^e + x_t^c\lambda_t^c\right) / |T|$$

$$s.t. (1) - (9) \tag{10}$$

Task assignment problem is known to be a classical NP-hard problem [23]. The proposed computational task assignment problem is an extension of the conventional task assignment problem due to the heterogeneous processing units and the parallel processing mechanism. Therefore, Metaheuristic approaches instead of exact methods are more suitable for solving this problem. Therefore, an adaptive artificial bee colony algorithm based on swarm intelligence is employed in this research.

V. SWARM INTELLIGENCE APPROACH

Swarm intelligence (SI)-based approaches are becoming increasing popular among various artificial intelligent algorithms, which were originally inspired by the collective behavior of natural species or animals, such as ant foraging, bee foraging, and fish schooling. SI is a relatively new branch of intelligent computation methods in contrast to the evolutionary computational methods. SI approaches use approximate and non-deterministic strategies to effectively and efficiently explore and exploit the search space in order to find near-optimal solutions [24], 25].

Among the various SI-based approaches, the artificial bee colony (ABC) algorithm exemplifies the classical features of SI, as decentralization, self-organization and collective behavior, which are necessary and sufficient to acquire intelligent performance [26]. Decentralization means that no central control mechanism exists. Self-organization of bees relies upon four fundamental properties, i.e. positive feedback, negative feedback, fluctuations and multiple interactions. Collective behavior refers to a bee colony, in which the individual behavior may be random, however the aggregation of individual behavior turns to be globally intelligent. In addition to the above three features, ABC algorithm has a simple control mechanism, for which only two parameters need to be tuned, which are the size of bee colony and a determinant criterion concerning whether one solution should be dropped or not.

As shown in Figure 5, the application of the ABC algorithm for solving the computational task assignment problem comprises four phases, i.e., the initialization phase, the employed bee phase, the onlooker bee phase, and the scout bee phase. A task set T, an edge server Set E, and a cloud server C are given in advance, with corresponding feature settings. In the initialization phase, all the tasks are randomly assigned to the edge servers or the cloud server. In the employed bee

```
Algorithm: ABC_TA
Input: Task set T, Edge server set E, Cloud server C
Output: Allocation of tasks to edge server and cloud
// initialization phase
s_i = {x_{i,1}, x_{i,2}, ..., x_{i,|T|}}
P = {s_1, s_2, ..., s_n}
fit_i = 1/(1 + f_i)
// iterative search
While termination conditions not met do
    // employed bee phase
    For all s ∈ P
        s' ← N(s)       // find proper reference
        s'' ← s⊗s'      // interact with the chosen reference
        s ← s or s''    // update the new solution
        τ_i = τ_i + 1|s ← s''
    End for
    // onlooker bee phase
    p_i = fit_i / Σ_{i=1}^{n} fit_i
    q_0 = p_0
    q_i = q_{i-1} + p_i
    If q_i ≥ r then
        Repeat the employed bee phase
    End if
    // scout bee phase
    If τ_i ≥ α then
        Reinitialize solution s_i
    End if
End while
```

FIGURE 5. Artificial bee colony algorithm.

phase, one employed bee searches the neighborhood area of a given solution for a better solution. If a better solution is found, the given solution will be replaced by the better one. In the onlooker bee phase, after acquiring the solution information from the employed bees, the onlooker bees determine to exploit some solutions probabilistically, which is realized by comparing a random number r and the cumulative probability q. Such a chosen probability is determined by the fitness of a solution. In the scout bee phase, if a solution cannot be updated after a certain number of iterations, it is regarded as exhausted, thus the scout bees abandon the exhausted solution and find another alternative solution. The three types of bees work collaboratively to find the optimal solution.

In accordance with the above workflow description of ABC_TA, s_i is a candidate solution comprising of a specific task allocation scheme as $\{x_{i,1}, x_{i,2}, \ldots, x_{i,|T|}\}$, in which $x_{i,j}$ indicates that task j is processed by server i. A number of candidate solutions compose a solution population as $P = \{s_1, s_2, \ldots, s_n\}$. f_i and fit_i are the objective value and fitness value of solution s_i correspondingly. In the employed bee phase, s' is another solution found in the neighborhood area of solution s. Solution s interacts with s' so as to generate a new solution s'', after that a solution selection mechanism is applied between s and s''. If the initial solution s is updated, its corresponding update times τ_i is set as 0, otherwise increase by one as $\tau_i = \tau_i + 1$. In the onlooker bee phase, the chosen probability p_i of solution s_i depends on its fitness value. The better fitness value, the higher chosen probability. Once s_i is chosen, it would go through employed bee operation one more time. In the scout bee phase, if the update times of solution s_i is greater than a predetermined criterion α as $\tau_i \geq \alpha$, solution s_i would be abandoned and replaced by a newly generated solution.

VI. PERFORMANCE EVALUATION

The test instances are generated in the following pattern. The length of tasks follows a uniform distribution within the range [1, 10] million instructions. The data volume of a task is assumed to be between 100 kilobyte and 10 megabytes. The affordable time delay of a task is assumed to be within the range between 100 milliseconds and 10 seconds. Concerning the edge server configuration, it is assumed that the average processing performance is 10 Million Instructions Per Second (MIPS), whereas the capacity of the cloud server is assumed to be 1000 MIPS. The connection between terminal devices and the edge server is through wireless communication methods, such as WiFi, Radio, and ZigBee. The connection between the edge server and the cloud is through broadband. The common mechanism is that tasks are assigned to a certain edge server with high probability, and forwarded to the cloud server if the edge server cannot provide sufficient resource for the given task within its expected time delay.

The proposed swarm intelligent approach is coded using Java with Eclipse IDE on a personal PC with a 3.6 GHz CPU and 16 GB RAM. The popularity of the ABC algorithm is partially due to its easy implementation and simple control mechanism, in which only two parameters need to be tuned, i.e., the size of the bee colony and the solution abandonment criterion. A large size bee colony indicates that a large number of parallel solutions could be operated simultaneously, which can increase the diversity of the search process. Comparatively, a large number for the abandonment criterion indicates that the search engine can exploit the promising search area in depth. Figure 6 and Figure 7 show the parameter analysis of the solution number (SN) and abandonment criterion α using a test instance with 200 incoming tasks. It is noted that the combination of $SN = 20$ and $\alpha = 100$ works well in contrast to other settings. Therefore, such a combination is employed in this research.

In order to examine the effect of the edge computing in the smart manufacturing system, more experiments were conducted with different numbers of incoming tasks under three different scenarios, i.e., cloud only, edge only, and mixed mode, which means the computational tasks are processed by the cloud server solely, the edge servers solely, and the mixed cooperation of the cloud server and edge servers, respectively. As shown in Fig. 8, the mixed mode outperforms the other two modes significantly. Along with the increasing number of tasks, the average processing time in cloud only mode fluctuate when the number of tasks is relatively small due

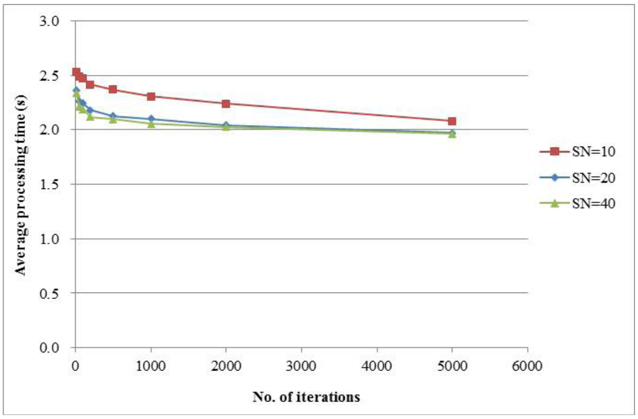

FIGURE 6. Performance measurement with different SN settings.

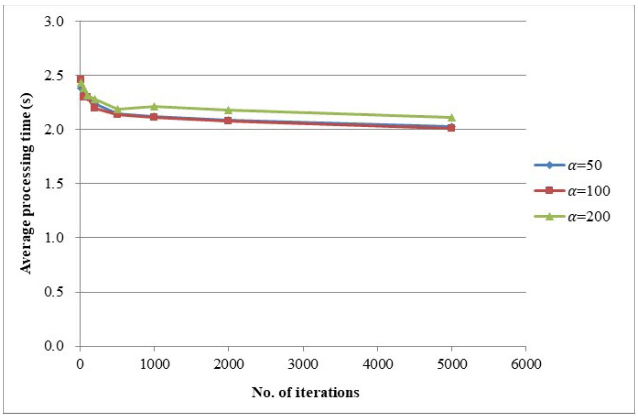

FIGURE 7. Performance measurement with different α settings.

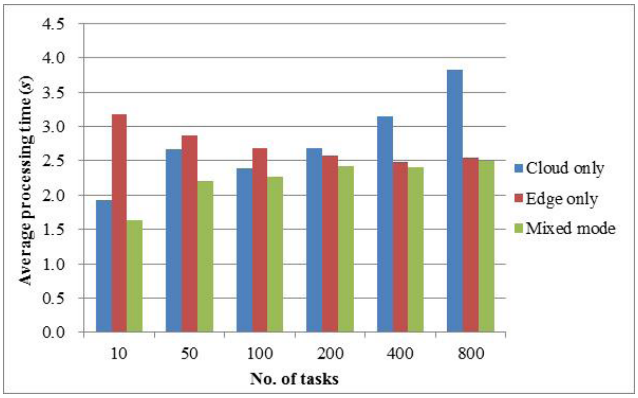

FIGURE 8. Performance measurement in different scenarios.

to the feature of random task load settings, and decreases gradually when the number of tasks increases to a certain large level due to the fixed available capacity of the cloud server. In contrast, the average processing time in the edge only mode does not vary significantly due to the requirement of the increasing number of edge servers along with the increasing number of tasks. In contrast to the cloud only mode and the edge server only mode, the mixed mode can save an average processing time around 17.16% and 16.52% respectively.

VII. CONCLUSION

Smart manufacturing is a promising future trend for the development of the production and manufacturing industry, which is the core of the new industrialization. The implementation of smart manufacturing needs the holistic support of information technology, data technology, and operational technology, among which the development of edge computing and blockchain technology based on the industrial internet can substantially facilitate the operational process of smart manufacturing. In this research, a conceptual integration of edge computing and blockchain technology is proposed to underpin the design of a smart manufacturing system. Moreover, the task assignment problem in the smart manufacturing system is formulated as an optimization model, and further solved using a swarm intelligence-based approach. Numerical experiments show that the introduction of edge servers outperform the other two mechanisms.

For future research, the application of the proposed smart manufacturing system needs to be further analyzed in-depth; especially field experiments should be conducted to collect on-site data, identify possible influencing factors, and adjust the parameter configuration of the proposed system and model. Moreover, the application of blockchain technology in both enterprise level and device level requires the design and development of an integrated transaction system, after that its effect can be quantified and further analyzed. In addition, more emerging technologies can be investigated to further serve the development of smart manufacturing.

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