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A Distributed Consensus Algorithm for Decision Making in Service-Oriented Internet of Things

Shancang Li, George Oikonomou, Theo Tryfonas, Thomas M. Chen, and Li Da Xu

Abstract—In a service-oriented Internet of things (IoT) deployment, it is difficult to make consensus decisions for services at different IoT edge nodes where available information might be insufficient or overloaded. Existing statistical methods attempt to resolve the inconsistency, which requires adequate information to make decisions. Distributed consensus decision making (CDM) methods can provide an efficient and reliable means of synthesizing information by using a wider range of information than existing statistical methods. In this paper, we first discuss service composition for the IoT by minimizing the multi-parameter dependent matching value. Subsequently, a cluster-based distributed algorithm is proposed, whereby consensus is first calculated locally and subsequently combined in an iterative fashion to reach global consensus. The distributed consensus method improves the robustness and trustiness of the decision process.

Index Terms—Distributed consensus algorithms, Internet of things (IoT), networks.

I. INTRODUCTION

THE INTERNET OF THINGS (IoT) has attracted much research attention from the academia and industry and is believed to enable the Internet to reach out into the physical world of Internet-connected devices [1], [2]. The IoT, as an emerging concept alongside this weave of technological advancements, refers to the connection of various physical objects in real life through wireless tags and sensors over network protocols similar to those used in the Internet [3]. Thus, smart objects can become part of the existing Internet. Built on the IoT, the physical world will become an intelligent world with smart physical objects tagged wirelessly and many fiction stories and scenarios become true [4], [5]. The recent development of Google Glass and Apple's *iWatch* rightly catch on this new technology trend. In the future internet concept, the existing Internet will become the backbone network where major data and information will be transferred and most objects in real life will be linked together pervasively [5].

Extended from the IoT, the concepts of *smart home*, *smart community*, *smart city* [5], and even the *smart planet* promoted by IBM suddenly become foreseeable in the near future [6]. The advances in wireless networks and data processing, such as cloud computing, wireless sensor networks, and wireless communications significantly enhance the traditional Internet into an intelligent IoT, capable of interconnecting diverse “things” into the physical world [7], [8]. In reality, the inexpensive intelligent sensor networks, radio-frequency identification (RFID) tags, and wireless devices are widely used to gather or collect data, making it possible to exchange and process information among objects [9]–[11]. This further leads to changes in the operations of many existing business information systems, such as enterprise systems and decision support systems [6]. In the foreseeable future, business processes and business model will also be changed and adapt to the IoT paradigm accordingly [3], [12], [13].

In the past few years, the IoT has attracted a lot of research attention and has achieved significant growth [13]–[15]. One concern lies in the communication and interaction process among different devices. The architecture of the IoT conceptually consists of three layers: *sensing layer* where many wireless sensors are located, *network layer* where data collected from sensors are transmitted, communicated, and processed, and *application layer* where various applications including business applications and enterprise systems access the functions and information provided by wireless sensors [9]. Different wireless devices may use different protocols with different object identification, information representation, and data transmission formats, raising the issue of processing information from multiple heterogeneous resources.

To tackle this issue, researchers have proposed service-oriented architectures (SOAs), built on top of the network layer so that data and information processing can be easily managed through different service components [7]–[9], [15], [17], [18]. In the SOA of the IoT, the interaction with and operations of different wireless devices are classified into different service components and the application layer software can access resources exposed by devices as services. These services are defined and classified based on real-world services, directly derived by physical world resources. Services are capable of sensing, processing and operating device entities by providing interaction interfaces or by generating events. The service-oriented IoT can thus control, manage, and interact with the real world by means of “services,” which enable bi-directional user-to-object information exchange and interaction [3], [16].

Existing research on service-oriented IoT have endeavored to contribute either from the architecture deploying perspective or the service classification, interaction, and discovery perspective.

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For example, Organero *et al.* [18] proposed a service-oriented platform for a personalized *e-learning* environment involving web 2.0-related service at an open and personal framework, while Vinoski [9] introduced several architectures of middle level in an IoT context, including a data collection model, a data mapping model, and a service encapsulation model. Liu *et al.* [7] investigated IoT-based mobile service deployments in support of the pervasive computing paradigm. Guinard *et al.* [17] proposed a service-oriented platform for IoT, in which a large number of service operations are involved, such as service discovery, query, classification, provision, and so on. The related services in the IoT can be combined into a complicate service, where a service can be operated as a modular, adaptive middleware component. Butt *et al.* have proposed a service discovery architecture for the IoT and its accompanying RESTful protocol. Their work targets severely constrained IoT deployments in terms of device processing power and network bandwidth [28], [29].

Further to the service platform, the architecture model for a service-oriented IoT is investigated in [17], where the author proposed a modeling method for collaborative virtual objects architecture via a generic way of interaction between services. However, little work has been done on the distributed consensus decision making (CDM) for services over IoT, which is of high importance in a context of resource-constrained wireless devices. Because the processing power and storage capacity of wireless devices in IoT is rather restricted, there is a high demanding for the discovery and coordination of services to efficiently process data and information over the IoT.

Therefore, there exist several challenges in current service-oriented IoT [3], [16], [17].

- 1) The IoT should be able to provide users with services for sensing information of interest, which might involve some operations of interconnected IoT edge devices. This imposes a challenge on efficient data propagation and reliable operation.
- 2) The IoT should be able to provide distributed CDM process for service detection, classification, composition, and data processing in a timely fashion.
- 3) Services should be able to cooperatively work to complete complicated tasks.

Information consensus between services should guarantee that each service share information over the IoT that is critical to the coordination task.

This paper aims at solving these challenges by proposing a distributed consensus algorithm for decision making of services at edge nodes in the service-oriented IoT. Specifically, the main contributions are summarized as follows.

- 1) A service provision framework is proposed, where the representation, discovery, detection, and composition of services are investigated and respective schemes are proposed.
- 2) A CDM method for service composition is proposed and can effectively select suitable services according to application layer requirements.
- 3) A distributed consensus algorithm is proposed which can provide robust decision results when multiple services are required to reach a global consensus.

The remainder of this paper is organized as follows. Section II addresses the architecture of the service-oriented IoT. Section III discusses the distribution of services in the service-oriented IoT. Section IV provides a decision support process which can automatically detect, discover, and classify IoT services. Section V proposes a distributed CDM method, while Section VI verifies the feasibility and effectiveness of proposed mechanisms. Section VII concludes the paper.

II. SYSTEM ARCHITECTURE OF SERVICE-ORIENTED IOT

This section aims at developing an effective architecture for service operations in the IoT, by extending pre-existing architectures and taking into consideration the unique characteristics of service-oriented approaches. The knowledge about services should be well represented and should be able to easily support discovery, detection, classification, composition, and testing of services. The IoT can be envisioned as a network of networks, in which smart “things” are connected to the Internet via heterogeneous access networks and technologies (such as sensor networks, mobile networks, RFID, etc.) to provide services and applications. In Fig. 1, a three-layer architecture of the IoT is summarized [1]–[6], [9], [11], [12], which contains three basic layers: 1) *the application layer*; 2) *the network layer*; and 3) *the sensing layer*. *The application layer* provides the functionalities that are built on top of an implementation of the IoT [2]–[4], [9], [11], [12], [14]. The application layer is connected with a business process modeling component for IoT-aware business processes which can be executed in the execution components. *The network layer* contains three basic components [5]–[7], [9]: 1) *service entity arrangements*; 2) *virtual entity (VE) and information*; and 3) *resources module*. The arrangement and access of IoT services to external entities and services is organized by the service entity arrangements component. The VE component contains functionality to associate VEs to relevant services as well as a means to search for such services. The resources module provides the functionalities required by services for processing information and for notifying application software and services about events related to resources and corresponding virtual entities. *The sensing layer* involves the sensing devices [5]–[9], such as RFID tags, smart sensors, etc., which can record, monitor, collect, and process observations and measurements. The network layer is able to access the sensing layer with device-level application programming interfaces (APIs), which provide the information exchange between the application and the real world.

Currently, there is a lack of standards for the architecture and information exchange over the IoT [2]–[4]. The application layer focuses on the application-level services by integrating IoT techniques with industrial expertise to achieve a wide range of services or applications; the network layer is based on the heterogeneous networks of IoT and communication techniques, such as sensor networks, mobile networks, and the Internet. The sensing layer involves the data acquisition and object identification, etc., which consists of a number of IoT edge nodes including RFID devices, intelligent sensors, wireless sensors, and other objects. Information exchange happens between these three layers to complete information perception, data

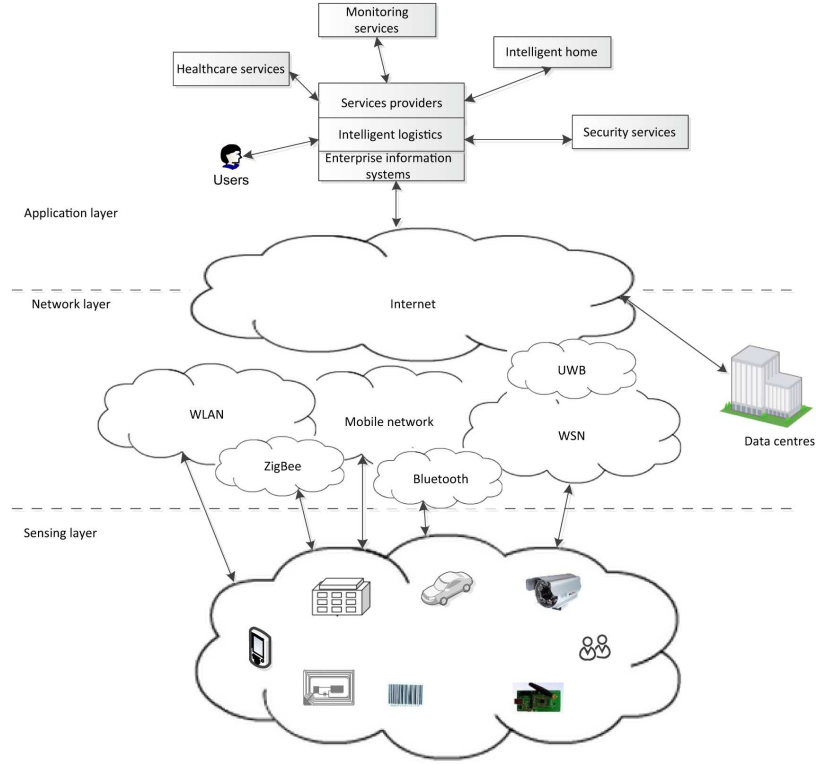


Fig. 1. Basic architecture of IoT.

acquisition, data processing, service performance, and the control of edge nodes. The information exchange includes the data exchange “vertically,” among the three layers, as well as horizontally between the IoT and cyber-physical systems. Researchers are still working toward optimal solutions to reduce the data communication overhead in both aforementioned planes.

The IoT has a service-oriented and context-aware architecture and is a mandatory subset of future Internet; every virtual and physical object can communicate with every other object providing their services seamlessly. The millions of devices in the IoT need to interoperate. Exposing each component’s functionalities as a standard service can significantly increase the efficiency of both network and device. In order to well organize the services provided by smart objects, each service should be able to find a virtual respective element in the IoT.

III. SERVICE DISTRIBUTION IN THE SERVICE-ORIENTED IOT

Services in a service-oriented IoT can be created and deployed according to the following steps [18]: 1) developing service composition platforms; 2) abstracting device functionalities and

communication capabilities; and 3) provision of a common set of services. In these phases, a *services identify management* process might be involved for context management and object classification, with which a mirror can be built in the service-oriented IoT for each object.

A service is a collection of data and associated behaviors to accomplish a particular function or feature of a device or portions of a device. As mentioned in [13], a *service may reference other primary or secondary services and/or a set of characteristics* that make up the service. *IoT services* can be categorized into two types: *primary* and *secondary*. The former denotes services that expose the primary functionalities at an IoT edge node, which can be seen as the basic component of a service and can be invoked by another service. A secondary service can enhance a primary or other secondary services by providing auxiliary functionality. A service may consist of one or more characteristics, such as service data structure, permissions, descriptors, and other attributes. In the IoT, a characteristic consists of the following segments [13]:

- 1) *characteristic declaration*, which describes the properties of the *characteristic value* (read, write, indicate, etc.), its handle and type [universally unique identifier (UUID)];

TABLE I
CHARACTERISTIC OF A SERVICE

Handle	Type	Permissions	Value
39	0x2800 (Service UUID)	Read	E0:FF
40	0x2803 (Characteristic UUID)	Read	10:29:00:E1:FF

- 2) *characteristic value*, which contains the value of a characteristic;
- 3) *characteristic descriptor*, which provides additional information about the characteristic.

Data are encapsulated in “Services” and exposed as “Characteristics.” Table I shows an example of a glucose level monitoring service. The service is assigned a UUID, such as 0x54656d70657261747572652053656e736f72 and the 0x2800 is the handle of the UUID, the value of the attribute at handle “39” is 0xFFE0, which is used for a glucose profile. The service includes all subsequent attributes up until right before the next service in the table.

When a device joins the IoT, it advertises its capability by broadcasting service advertisements with information about services it can provide. Upon receiving the message, other devices already present in the deployment can get these services registered as IoT services by exchanging service information [14]. In doing so, a hierarchical overlay can be obtained with periodic service advertisement messages. Due to the dynamic nature of the IoT, the structure of the hierarchy can change frequently.

IV. SERVICE DISCOVERY AND CLASSIFICATION

A. Service Discovery

In service-oriented IoT, many of the services profiles are designed using a traditional client/server (C/S) approach. In this context, “Server” nodes have data to make available to other nodes. A “Client” node may be a device that needs information from a server. In traditional C/S architecture, a client initiates communication with a server by performing the following steps: at first, a client has to locate an appropriate server device, in the IoT this is done using the inquiry process. Then, the client sends out messages looking for nearby nodes. Server nodes which are listening for these messages respond to the client. This allows the client(s) to create a list of candidate servers.

B. Services Classification

The classification for a priori analysis is necessary in the service-oriented IoT. Assume $\{w_1, w_2\}$ is a finite set of two states of IoT nodes. The state of nodes includes classes or categories of objects.

Services classification in the IoT includes expedient objects, intelligent objects with more computing power, e.g., active tags, sensors; nonexpedient object, objects with limited computing power, e.g., passive tags. Other possible parameters for object classification include *size, mobility, power, physical/logic object*, etc.

Applications of decision theory on object classification can yield a novel solution. It works under uncertainty which is best suited for an IoT context with two scenarios in which object will communicate when the probabilities of expedient and nonexpedient objects are known or completely unknown.

The uniqueness of this solution is an application of *Bayesian decision theory* (BDT) with optimization on binding a posterior value for the expedient object and thus making the selection procedure proficient.

C. IoT Service Aggregation

When a service is well classified, it can be properly integrated into the IoT. This process needs an agreement among involved nodes, which can be perceived as a distributed consensus problem. For one node, the discovered service s_1 can be combined with existing service(s) to form a complex service s_2 according to the following conditions:

$$s_1.\text{output} \cong s_2.\text{input} \quad (1)$$

$$\xi_s(s_2.\text{output}) \succ \xi_s(s_1.\text{input}). \quad (2)$$

The first condition ensures that the output of service s_1 can be consumed by s_2 . The second condition states that the output of s_1 can be completely accepted by s_2 . Actually, when the discovered service is available for multiple IoT edge nodes, then a distributed CDM process is needed to get it efficiently combined into the service-oriented IoT. In this paper, we define a normalized matching value x_{match} to evaluate the matching of the new coming s_1 with the existing $K (K \geq 1)$ services based on multi-attributes

$$x_{\text{match}}(s_i, s_j) = \text{match}(s_i, s_j), \quad j = 1, \dots, K \quad (3)$$

in which the function $\text{match}(s_i, s_j)$ is used to evaluate the similarity of services s_i and s_j in terms of critical parameters such as *position, QoS requirements, availability, robustness*, etc.

V. DISTRIBUTED CDM OF SERVICES

In an IoT context, it is important to get an agreement when an event can be accessed by multiple IoT edge nodes, which is known as CDM [18]. In CDM, the input and ideas of all IoT end nodes are gathered and synthesized to arrive at a final decision acceptable by all. By means of consensus, a better solution can be achieved and the trustiness between nodes can be promoted. Normally, two kinds of consensus situations are involved in the service-oriented IoT [19].

- 1) Data consensus, whereby multiple services must reach consensus when referring to the same piece of data. For example, when temperature at a specific location can be provided by multiple IoT edge nodes, then a data consensus will increase confidence on the measurement result.
- 2) Service consensus, which helps the IoT to build composition services with multiple services provided by different IoT edge nodes.

For the former, a number of distributed consensus algorithms have been developed. The latter can be implemented based on distributed consensus service composition.

A. Consensus Problem in the IoT

In practice, global consensus might be needed to facilitate knowledge sharing or service integration [19]. In this section, we will propose a distributed consensus method to enable each IoT

edge node to develop a local consensus when needed. The IoT network can be partitioned into multiple clusters and a local consensus can be achieved within each cluster, and can then be used to make consensus decision in knowledge sharing and integration of functional capabilities.

In forming a local consensus, an assumption made here is that the services being merged are in similar domains where a quantitative criterion can be used to evaluate the composition's feasibility. A new service can become part of a *service pool* when a consensus or agreement can be achieved for all involved IoT edge nodes. The proposed matching value-based method allows one to find the possibility that the services can be composed by existing IoT services [20], [21]. Therefore, matching values at nodes are gathered and synthesized to reach a final decision acceptable by all. Through consensus-based decision making, services in IoT are not only working to achieve better solutions, but also to promote trust [22], [23].

1) *Consensus Updates*: An IoT network can be well modeled by a graph $G = (\mathbf{V}, \mathbf{E})$. Let $x_v(t)$ represent the state value (used to evaluate the matching value for new incoming services) at node v at time t , which can be intuitively understood as the estimate of the consensus value of v . At each node $v (v \in \mathbf{V})$, let $x_v(0)$ denote the initial measured value at v , which can be further updated through iterative exchanges between neighbor nodes and the consensus or averaging can be achieved at all the nodes

$$x_v(t+1) = x_v(t) - \mu \sum_{u \in \mathbb{N}_v} (x_v(t) - x_u(t)) \quad (4)$$

in which $\mathbb{N}_v$ denotes the neighbor list of v and μ denotes the *step size* in each iteration. The convergence properties of (4) are largely determined by the Laplacian matrix $\mathbf{L}$, thus

$$\mathbf{L}(t+1) = f(x) = \begin{cases} d_v, & u = v \\ -1, & (u, v) \in \mathbf{E} \\ 0, & \text{else} \end{cases} \quad (5)$$

in which d_v is the degree at node v . Let an $n \times 1$ vector $\mathbf{x}(t)$ denote the states vector of all nodes at time t , then (4) can be formatted as

$$\mathbf{x}(t+1) = \mathbf{x}(t) - \mu \mathbf{L} \mathbf{x}(t) = (\mathbf{I} - \mu \mathbf{L}) \mathbf{x}(t). \quad (6)$$

It can be rewritten as

$$\mathbf{x}(t+1) = \mathbf{W} \mathbf{x}(t) \quad (7)$$

in which $\mathbf{W} = \mathbf{I} - \mu \mathbf{L}$. For a graph G , its *Laplacian matrix* $\mathbf{L}$ with eigenvalues $\lambda_0 \lambda_1 \dots \lambda_{(n-1)}$ and λ_0 is always 1 because every Laplacian matrix has an eigenvector $\xi_0 = [1, 1, \dots, 1]$.

B. Local Distributed Consensus Algorithm

An IoT can be easily grouped into multiple *clusters* by well-known clustering algorithms, such as *LEACH* (low-energy adaptive clustering hierarchy), *FCM* (fuzzy C-Means),

location-based clustering, *HSA* (harmony search algorithm) [22]–[25], etc. With these algorithms, a deployment can be broken down into clusters according to application requirements such as *energy consumption*, *information types*, *location*, *QoS attributes*, etc. In each cluster, a node is selected as cluster head (CH) and is able to exchange information with other CHs. Assume a deployment of K clusters $\{C_1, C_2, \dots, C_K\}$, then each cluster C_i consists $|C_i|$ nodes. For a cluster C_k , the *consensus problem* can be formulated as

$$\mathbf{x}_k(t) = (\mathbf{I} - \mu_k \mathbf{L}) \mathbf{x}_k(t-1), \quad k = 1, \dots, K. \quad (8)$$

At each CH, the iterative averaging problem can be concurrently solved and for each cluster a *local consensus or agreement* can be achieved

$$\mathbf{x}_k(t) = (\mathbf{W}_k)^t \mathbf{x}_k(0), \quad k = 1, \dots, K \quad (9)$$

here we have

$$\lim_{t \rightarrow \infty} \mathbf{x}_k(t) = \lim_{t \rightarrow \infty} \mathbf{W}_k(t) = \mathbf{x}_k(0) \mathbf{1}, \quad k = 1, \dots, K \quad (10)$$

in which $\mathbf{1}$ denotes the vector with all coefficients one. According to [15], the convergence rate can be measured by

$$\rho(\mathbf{W}_k - \mathbf{1} \mathbf{1}^T / |C_k|) \quad (11)$$

and the associated convergence time is

$$\tau = \frac{1}{\log(1/\rho)}. \quad (12)$$

Then, the problem can be solved as K concurrent subproblems

$$\min \rho(\mathbf{W}_k - \mathbf{1} \mathbf{1}^T / |C_k|) \quad (13a)$$

$$\text{s.t. } \lim_{t \rightarrow \infty} \mathbf{W}_k = \mathbf{1} \mathbf{1}^T / n \quad (13b)$$

$$\mathbf{W}_k \mathbf{1} = \mathbf{1}. \quad (13c)$$

VI. GLOBAL DISTRIBUTED CONSENSUS ALGORITHM

Similarly, a *global consensus* can be obtained $\mathbf{x}_g = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_K]^T$

$$\mathbf{x}_g(\tau) = \mathbf{W}_g^T \mathbf{x}_g(0) \quad (14)$$

in which $\mathbf{x}_g(0) = [\mathbf{x}_1(t), \mathbf{x}_2(t), \dots, \mathbf{x}_K(t)]^T$. Equation (13) can be solved by

$$\min \rho(\mathbf{W}_g - \mathbf{1} \mathbf{1}^T / |C_g|) \quad (15a)$$

$$\text{s.t. } \lim_{t \rightarrow \infty} \mathbf{W}_g = \mathbf{1} \mathbf{1}^T / n \quad (15b)$$

$$\mathbf{W}_g \mathbf{1} = \mathbf{1}. \quad (15c)$$

The convergence time of the whole problem can be

$$\tau = \max_{k=1, \dots, K} (\tau_k) + \tau_g. \quad (16)$$

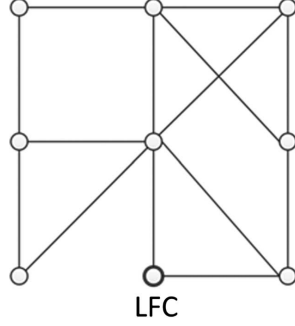


Fig. 2. Randomly built connected cluster.

A. Global Distributed CDM

Provided that $\mathbf{x}_g(t)$ is available at all CHs, the CHs can have the following hypothesis testing:

$$\mathbf{H}_0 : \mathbf{r}(t) = \mathbf{x}_g(t) \quad (17a)$$

$$\mathbf{H}_1 : \mathbf{r}(t) = \mathbf{s}(t; \mathbf{p}) + \mathbf{x}_g(t) \quad (17b)$$

in which $\mathbf{s}(t; \mathbf{d})$ denotes the judgement vector at nodes and $\mathbf{p}$ denotes decision parameters (e.g., distances $\mathbf{d}$). According to our previously published work in [15], for given $\mathbf{x}_g(t)$, using the *likelihood ratio* with a decision threshold ξ , we can have the following decision rule, which is called the *likelihood ratio* test:

$$\text{accept } \mathbf{H}_0 : \text{if } \frac{f_0(\mathbf{r}(t))}{f_1(\mathbf{r}(t))} > \xi \quad (18a)$$

$$\text{accept } \mathbf{H}_1 : \text{if } \frac{f_0(\mathbf{r}(t))}{f_1(\mathbf{r}(t))} < \xi \quad (18b)$$

where $f_i(\mathbf{r})$ is the likelihood function under $\mathbf{H}_i$ and is defined in our previous work [16].

Let $v_k(t) \in \{0, 1\}$ and $d_k(t)$ be the local decision at the K th CHs at time t , respectively. Then, we have

$$d_k = \ln \frac{\Pr(v_k(t)|\mathbf{H}_1)}{\Pr(v_k(t)|\mathbf{H}_0)}. \quad (19)$$

VII. SIMULATION

In order to evaluate the proposed distributed consensus algorithm, we simulated an IoT network with 100 nodes deployed in a 100×100 area. For simplicity, the network is clustered into nine using a distance-based static clustering scheme. Each cluster selects one node as local fusion center [LFC, it is also named cluster head (CH)] which can communicate with its neighbors within the cluster. At time instant t , the nodes within a cluster distributively calculate the *local consensus* and measurements on each node are updated accordingly. By doing this, each LFC keeps record of the *local consensus* calculated within its cluster. Similarly, LFCs exchange *local consensus*es and form a *global consensus*, with which a global decision can be made. Fig. 2 illustrates a connected graph which denotes a cluster, in which

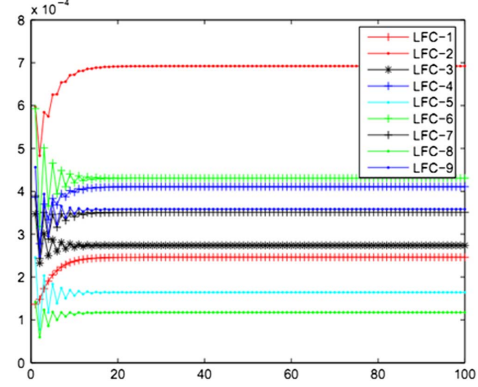


Fig. 3. NMSE of local consensus results.

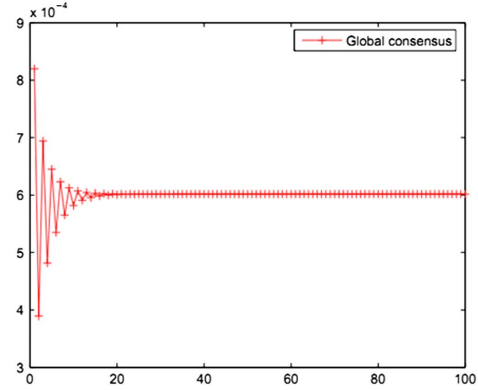


Fig. 4. NMSE of global consensus results.

the LFC is labeled. Each cluster contains nine nodes, these nodes cover a grid area of approximately (10×10) and distributively detect chemical and biological (CB) emissions. There are nine clusters able to cover the entire (100×100) area. Each cluster executes the distributed consensus algorithm to iteratively calculate its local consensus value. The normalized mean squared error (NMSE) can be used as a performance measure [19]

$$\text{NMSE} = \frac{\mathbb{E}[\|\mathbf{x} - \mathbf{x}_{\text{consensus}}\|^2]}{\mathbb{E}[\|\mathbf{x}\|^2]}. \quad (20)$$

Fig. 3 shows the NMSEs at nine LFCs when service matching values are to be estimated using the above iterative distributed algorithm in each cluster. It is noted that the distributed consensus converged very fast. LFC-8 achieved the highest convergence speed by reaching a local consensus value (1.15) within 11 s. All other LFCs converged to a local consensus value within 17 s. The nine LFCs are able to freely communicate and can form

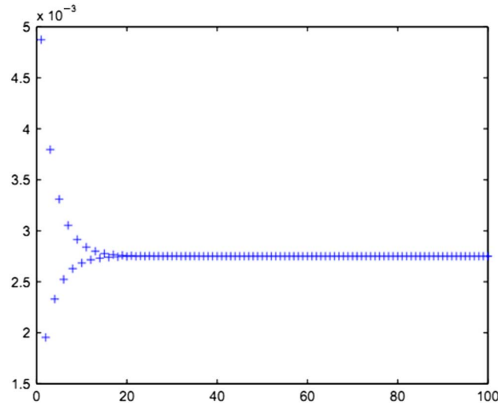


Fig. 5. Global consensus result at LFCs vs iteration number.

a connected sub-network, meanwhile each LFC holds a local consensus calculated within its own cluster. Iteratively, a global consensus can be reached from the nine LFCs. Fig. 4 shows the NMSE of global consensus result, which converges to a global consensus value (6.02) within 20 s. In Fig. 5, we display the results of the evaluation of the proposed algorithm's computational cost. Results show a stable global consensus is reached within 18 iterations, which is reasonable for a network of this size.

VIII. CONCLUSION

IoT has attracted much research attention in recent years [30]–[35]. The advances in wireless sensor networks, cloud computing, and other technologies help move the traditional Internet to an intelligent IoT [36], [37]. This trend will lead to further changes in existing systems such as enterprise systems [38]–[40], decision support systems [43]–[47], as well as business processes in general [47]–[49]. In this paper, we have presented a distributed CDM method for service detection, classification, composition, and data processing for the IoT. Our proposed algorithm aims to improve the trustiness and efficiency of distributed average CDM. We first propose a three-layer service provisioning framework for service-oriented IoT deployments, which is able to represent, discover, detect, and compose services at edge nodes. The proposed CDM method for service composition enables services to make decisions based on application layer requirements. Subsequently, a distributed consensus algorithm is proposed to provide robust decision results when multiple services are involved to reach a global consensus. Simulation results show the proposed method's effectiveness and performance. As part of our future research, we aim to develop more comprehensive services covering all phases of the service lifecycle. The objective is to provide the service-oriented IoT with interactive and collaborative methods for the realization of more intelligent and ubiquitous information exchange and resource allocation in dynamic environments.

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