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Exploiting Industrial Big Data Strategy for Load Balancing in Industrial Wireless Mobile Networks

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ABSTRACT In the era of big data, traditional industrial mobile wireless networks cannot effectively handle the new requirements of mobile wireless big data networks arising from the spatio-temporal changes of a nodes traffic load. From the perspective of load balancing and energy efficiency, industrial big data (IBD) brings new transmission challenges to industrial wireless mobile networks (IWMNs). Previous research works have not considered dynamic changes related to the traffic and mobility of IWMNs. In this paper, using an IBD technique, we propose a novel second-deployment and sleep-scheduling strategy (SDSS) for balancing load and increasing energy efficiency, while taking the dynamic nature of the network into consideration. SDSS can be divided into two stages. In the first stage, changes in the traffic of every network grid and its maximum traffic load at different times are calculated using big data analysis techniques. In the second stage, a second-deployment method for the cluster head nodes (CHNs), based on each grids maximum traffic load, is adopted. To save energy, based on their position and traffic states, a sleep-wake scheduling is presented for the CHNs. Simulations results verify the effectiveness of this methodology to save energy and obtain a traffic balance, which is more efficient than obtained through traditional methods.

INDEX TERMS Load balancing, energy efficiency, sleep scheduling, second-deployment, industrial wireless networks, big data networks.

I. INTRODUCTION

Industrial big data networks have become a subject of broad interest in the domains of smart factories and industry 4.0 [1], [2]. There are several factors which have led to this trend [3], [4]. First, with the wide-spread adoption of wireless communication technologies, there has been a vast increase in the number of multimedia equipment and sensors that have joined the communication networks. Secondly, with the emerging of frameworks in the context of industry 4.0, smart factories, smart manufacturing, M2M (Machine to Machine) communication, and M2S (Machine to Server) communication, more and more wireless links are being involved in data transmission and communication [5]–[7]. Thirdly, as more devices are entering the system, it is leading to an increase in the variety of data and sources. This has exerted new challenges for wireless big data networks in terms of mobility, size of the data, and diversity of the datasets. These challenges are more marked in Cluster-based wireless networks (CWNs), in particular for cluster head nodes (CHNs). Among these challenges, traffic balance and energy efficiency are the most significant ones.

In the domain of smart communication, there has been a constant increase in the variety of mobile nodes joining the networks. Especially, in the industrial domain, we are seeing an increase in the number of mobile phones, mobile robots, AGVs (Automated Guided Vehicles), and other mobile devices being connected over wirelessly. Mobile wireless networks have proved to be an effective way of dealing with this rise of increased mobility, flexibility, and extendibility, especially in Industry 4.0 factories [8]. However, managing large-scale deployments of static and mobile nodes is a challenging task. Recently, Cluster-based wireless networks (CWNs) which are composed of a subsystem of cluster head nodes (CHNs) and common nodes (CNs) have emerged to address this challenge. CWNs play an important role in network management. Serving as access points and sink nodes, they have become the key nodes for the whole system. CWNs structure is widely adopted into the IWMNs for network cushy and centralized management. However, load balance and energy efficiency still need to solve for CWNs in context of big data. In [9]–[11] and [12], for increasing the real-time performance and balancing the load of the wireless network, the authors use an optimization method to identify the most efficient routing line. In [13], [14] and [15], heuristic algorithms are adopted for energy saving in wireless network with applications in the domain of big data. Hava *et al.* [16], Das *et al.* [17], Moghadam *et al.* [18], Tokito *et al.* [19], and Kim *et al.* [20] have researched on how to perform traffic load balancing in wireless big data networks. Although, all of these mentioned works of research have tried to address the problem from different layers, these studies are based on the static space-time condition, and only a few works of research have considered the dynamic parameters at play; such as the type of wireless protocol, the radio frequency, and the characteristics of the data, among others.

Most related works on wireless big data, have investigated optimization of traffic balancing and energy saving separately. However, in the industrial domain, the traffic load is dynamic and changes with time. This is caused by the dynamic number and state of the mobile nodes and traffic load of the nodes present in an industrial wireless network. Therefore, existing approaches and algorithms are not applicable in practical scenarios in the industrial domain. In industrial applications, the traffic load of the network in the presence of big data will change with time because of the changes in the mobile nodes and the communication activities.

While the use of big data brings advantages and conveniences, it also raises multiple challenges to be addressed in the framework of smart factory and industry 4.0. In this paper, we aim to address some of these challenges. Our objective is to develop an algorithm with the following properties: 1) The algorithm can balance the dynamic changes in the traffic load; 2) The algorithm is energy efficient. Hence, in the paper, we propose a new second-deployment strategy based on the timing feature of the network load. To save energy, we adopt a sleep-wake scheduling approach, based on the location and the traffic load of the access nodes. Through the results of our simulations, we verify the efficacy of this proposed methodology and demonstrate that it can improve the energy efficiency and achieve traffic balance. The proposed method presented in this paper is summarized as follows:

1) Based on industrial big data strategies, the network domain is divided into several grids. The changes in the traffic balance in every grid at different time are identified using an SVM (Support Vector Machine). Next, iterating over every grid, the maximum traffic load in the time domain is identified.
2) Using the Distributed Genetic Algorithm (DGA) we obtain a good traffic balance level, and second-deploy the cluster head nodes according to every grids maximum traffic load. To save energy, based on their positions and traffic load, a sleep-wake scheduling for the access nodes is adopted.
3) We construct simulations to evaluate the performance. Simulations results verify that the proposed methodology can effectively save energy and yield a better traffic balance than traditional methods.

The remaining part of the article is organized as follows. After providing an overview of the framework of the second-deployment and sleep scheduling for industrial wireless networks, we introduce the system design based on time graph theory. Next, we demonstrate our algorithm and methodology. Then we discuss the performance of our method and compare it with that of related strategies. Finally, we summarize our work with a short discussion.The remaining part of the article is organized as follows. In section II, a related works are introduced. After providing an overview of the framework of the second-deployment and sleep scheduling for industrial wireless networks, we introduce the system design based on time graph theory. Next, we demonstrate our algorithm and methodology. Then, we discuss the performances of our method and compare it with that of related strategies. Finally, we summarize our work with a short discussion.

II. RELATED WORKS

This section provides a review of the related works of literature. We group the related works into three different categories: 1) Big data in wireless networks; 2) load balancing strategies; and 3) sleep scheduling in wireless networks. Investigating the works of research in these categories provides us with useful and valuable references for our scheme.

A. BIG DATA IN WIRELESS NETWORKS

Recently, the exponential growth in data services has ushered in the big data era and emerging wireless network technologies have started to embrace big data. Big data technologies provide both new opportunities as well as raise new challenges for wireless networks. A wide range of massive data is continuously generated, gathered and stored in wireless networks by wireless devices [21]. While network technologies must address challenges and develop strategies to manage this data deluge, big data has also opened up new opportunities to improve the network efficiency. These opportunities have attracted the attention of both academia and industry and research is being conducted from different perspectives. In [22], by adopting machine learning and other tools, the authors combined big data with spatio-temporal information to analyze anomalous behaviors in mobile wireless networks. Fan *et al.* [23] proposed a bandwidth allocation algorithm, which used collected user and network data to provide efficient bandwidth usage and improve the throughput of a cellular network. There has been a great deal of research for optimizing networks using big data [24], [25]. Bi *et al.* [26] reviewed state-of-the-art signal processing methods and networking structures, and discussed the challenges and opportunities. Zeydan *et al.* [27] proposed a big data enabled architecture using edge computing to tackle the two main challenges for wireless networks, namely processing and wirelessly communicating the huge amount of available data.

B. LOAD BALANCE STRATEGIES

Load balancing has been an important and heavily researched topic in networks and is a key performance indicator for wireless networks. The load balance scheme used by a network directly affects the performance factors such as network life, and latency. Therefore, many researchers have studied this topic from different network layers. Efficient load balancing involves adopting different strategies to create optimal routing paths for transmitting network traffic. So and Vaidya [28] proposed a routing protocol that considers the network connectivity to find routes to balance load among the available channels. Alghamdi [29] proposed a load balancing multi-path routing protocol based on maximal minimal nodal residual energy. So and Byun [30] presented a new routing protocol called the Least Common Multiple based Routing to perform load-balanced multi-path routing in Mobile Ad hoc networks. Meanwhile, there has been a great number of studies to achieve better load balance using the medium access control (MAC) layer. Zhao *et al.* [31] proposed a distributed connection admission control scheme based on IEEE 802.11-mesh networks. The scheme incorporated load balancing while selecting a mesh path for a new connection. In [32], a load-balancing based medium access control scheme for wireless network with multiple channels available which could dynamically assign channels to mobile nodes was presented. However, the aforementioned studies mainly focus on a static network, without considering the dynamically changing network environment which can be particularly observed in a mobile wireless network.

C. SLEEP SCHEDULING

A major bottleneck for wireless networks is the limited availability of energy. Due to heavy memory and efficiency needs, this is a major issue in industrial wireless big data networks. Efficient sleep scheduling is an efficient mechanism to conserve energy of wireless systems, and therefore many researchers have focused to develop efficient sleep strategies. Current sleep methods mainly utilize the MAC layer. Anastasi *et al.* [33] presented an adaptive staggered sleep protocol for efficient power management in wireless sensor networks. The protocol dynamically adjusted the sleep schedules of nodes to match the network demands, even in time-varying operating conditions. Jurdak *et al.* [34] introduced an adaptive radio low-power sleep mode based on current traffic conditions in the network in the physical layer. In recent years, sleep schedules have also been introduced into industrial wireless networks. Mukherjee *et al.* [35] provided a sleep scheduling scheme to ensure the requirement of coverage degree to monitor dangerous levels in a toxic gas leakage area, while maintaining global network connectivity with minimal awake nodes. Although a great number of studies have aimed to solve the challenge of optimizing the energy efficiency by adopting sleep mechanisms, few works have concentrated on clustered/group-based industrial wireless networks under sleep mode.

III. ARCHITECTURE OF INDUSTRIAL WIRELESS MOBILE NETWORK FOR BIG DATA

Big data and wireless technologies play important roles in providing flexibility and intelligence in the domains of smart factory and industry 4.0. With the increase in deployments of smart factories, we have come to observe that traditional networks no longer meet the mobility and flexibility requirements of the system. Industrial big data and industrial wireless mobile networks enable an effective path for this new industrial framework. In recent years, there has been an increase in the adoption of mobile robots, vehicles, AGVs, and workmen in industrial settings. In the light of this increased modernization, static wireless networks can no longer be considered suitable for handling this increased load. To handle this, mobile wireless communication has gradually entered as the solution. However, industrial mobile wireless networks, in the context of big data in Industry 4.0 and smart factories, still face two challenges. First, the presence of big data means that the industrial wireless networks must handle an increase in the load with respect the size and speed of the data being transmitted. Secondly, these networks must also deal with the dynamic properties of the data in terms of changes in mobility and states of the network nodes.

As shown in Fig.1, in the industrial domain, the traffic load may change with time. Fig.1(a) shows the system at the current time t_i, and Fig.1(b) shows the network traffic load at the following time t_{i+1}. We can observe that, in the presence of big data, the traffic of an industrial wireless network, changes over time with the change in the number of mobile nodes and the traffic load of the nodes. Therefore, we must adopt a novel approach to address this problem. Fig.2 represents a framework of IWNs for big data and provides an overview of our method. As shown in Fig.2, the whole industrial domain is divided into multiple grids by size or other parameters. In the system, the clustering/grouping framework is applied to the network. The development of the system of industrial wireless network with a big data working mechanism is composed of three steps: data gathering, big data analysis, and our proposed algorithm (Distributed genetic algorithm).

A. DATA GATHERING

The key parameters (e.g. balance, working states, and positions of devices such as robots, AGVs, machine, sensor nodes, workmen) are transmitted to the cluster head nodes. As shown in Fig.1, all nodes are linked via wireless radio. Meanwhile, the network devices also upload the state of every node (including position, load, etc.) at different times and in different grids. Meanwhile, these sensing data are transmitted by the backbone network and stored in a big industrial data center.

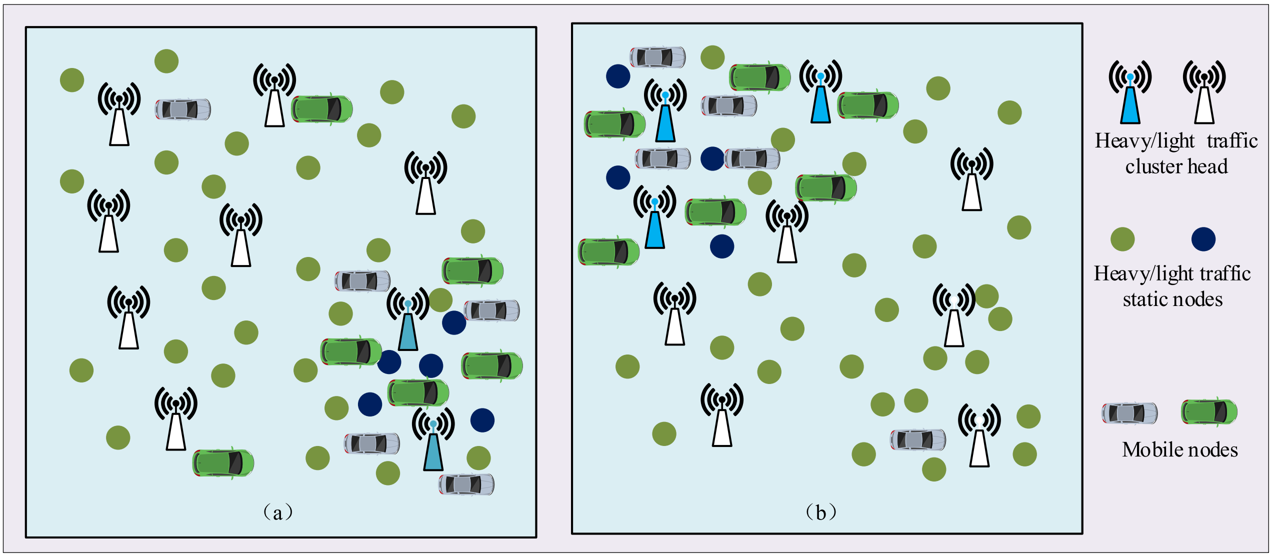

FIGURE 1. The traffic load changes in the industrial wireless big data network with time. (a) shows the system at the current time t_i; (b) shows the network traffic load at the following time t_{i+1}.

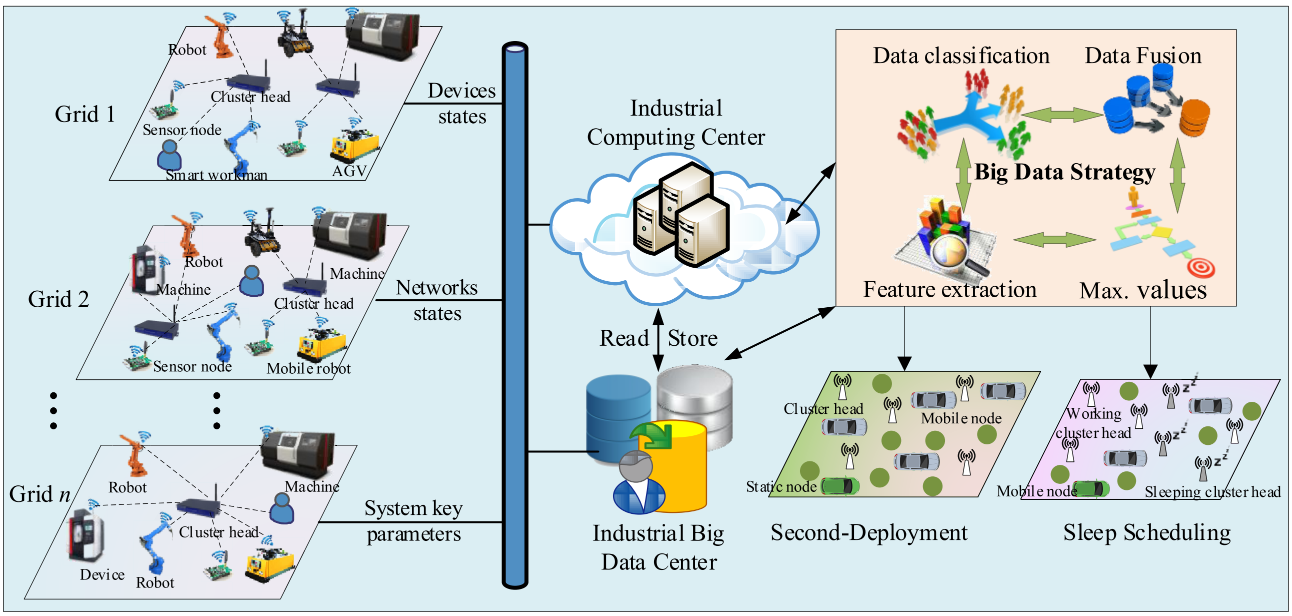

FIGURE 2. The overview of the proposed method.

B. BIG DATA ANALYSIS

In this setup, the purpose is to identify the changes in the network. This is done by mining the big data collected from the different locations at different times. The key parameters of the network, especially those of the key nodes, are identified from the big data and stored into specific databases. Next, a mathematical model of the network is built to identify the cluster head, ordinary nodes, mobile nodes and corresponding traffic loads for each grid. This extraction is done for different time periods using advanced analytic methods consisting of data fusion and classification algorithms. Then, the traffic load and features from the time domain data of the network are analyzed. Finally, the maximum traffic load in the time domain for every grid is identified by searching through the big data analysis results.

C. DISTRIBUTED GENETIC ALGORITHM

In this setup, we aim to design the specific algorithm according to the networks feature based on the results of the big data analysis. In detail, we apply a distributed genetic algorithm to each grid to obtain an optimal traffic balance level. Based on this, we present the second-deployment of the CHNs to maximize every grids traffic load. Then, to save energy, a sleep-wake scheduling,

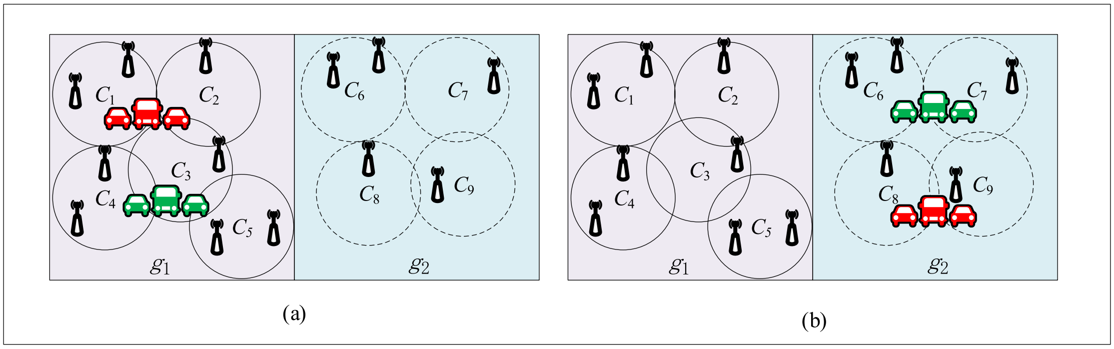

FIGURE 3. Illustration of traffic load change for different time periods. a) the communication load in grid g_1 and g_2 at the time T_i; b) the communication load in grid g_1 and g_2 at time T_{i+j}.

based on the position and traffic load of the access nodes, is adopted.

In industrial wireless mobile networks, for dealing with dynamic changes causing by industrial big data transmissions, we propose a new second-deployment strategy based on the time feature of the network load. This strategy balances the traffic and saves energy under the mobility conditions. SDSS can be divided into two stages. The first stage aims to search every grid for the maximum traffic load. The second stage is to identify a second-deployment based on a sleep-wake scheduling of the cluster head nodes.

IV. INDUSTRIAL BIG DATA STRATEGY FOR LOAD BALANCING

In the section, we introduce our strategy for load balancing. First, we describe the dynamic network system. Then, to obtain the network features, we design a technique called the Search the Heavy Traffic Load Grids and Time period (SHTGT) method. Finally, we provide the second-deployment and sleep scheduling methodology.

A. DYNAMIC NETWORK SYSTEM DESCRIPTION

Consider an industrial (for example: smart factory) area A with multiple wireless groups. Let us suppose that the deployment area is divided into m grids. Each grid g_i has N_g cluster head nodes for supporting access service. During a period of time T_i, there are N_s^i static nodes and N_m^i mobile nodes. For each cluster or group, the cluster head node C_i in A, for $i = 1, 2, \ldots, N_c$, is deployed at a uniform point, and is responsible for uploading or downloading the group members sensing data or control information. In the communication cluster C_i, within a period of time T_i, there are N_s^i static nodes and N_m^i mobile nodes. Each node (static and mobile) is represented by a circle centered at the related deployment point or moving path with a uniform radio transmission R. We use w_s^i and w_m^i to indicate the traffic loads of the static and mobile nodes in T_i respectively. We can observe that the total traffic load W_i for the cluster head node C_i can be represented as $w^i(N_s{+}N_m)$ when every node has the same traffic load w_i. Meanwhile, we know that for different periods of time, the traffic loads can be different. So, first, to deal with heavy traffic, a new group leader needs to be deployed. Next, to increase the energy efficiency, when some group leader chooses to serve the ordinary nodes, the others should go into sleep mode.

A large number of mobile nodes are deployed to increase the mobility and flexibly of the network. When the network nodes are moving, their positions, and the traffic load of the communication group changes dynamically. When a large mobile node enters the coverage area of a group leader, it can cause a peak in the traffic load for the group leader. In such a situation, the whole network will face a severe increase in load and this might lead to an energy unbalance. So, the first problem that needs to be addressed by the second deployment is related to this load change. In order to simplify the problem scenario, we assume that there are two grids g_1 and g_2 in A, and those grids share the same framework and communication system. Therefore, all the clusters can be reduced into a simple pattern as shown in figure Fig 3. At first, during time T_i, all nodes rest in g_1, and the cluster heads nodes C_1, C_2, C_3,C_4, C_5 provide the necessary access service. As shown in Fig. 3b, during time T_{i+j}, most mobile nodes leave g_1 and enter g_2. Therefore, at T_{i+j} there will be a network traffic jam in g_2 among C_6, C_7, C_8, C_8.

Let us suppose each cluster node is equipped with a battery with limited power, and has two states: active and sleep. Only the active state consumes energy, while the sleep state does not consume power. Therefore, the task of traffic load balancing can be divided into three sub-tasks. The first subtask is executed to identify the heavy load times, amounts and grids based on the load threshold. The threshold can be adjusted according to the application. Since in our example, the pattern is simplified as consisting of two grids, this work aims at finding the heavy load times T_1 and T_2 with heavy load amounts w_1 and w_2 for grids g_1 and g_2, respectively. Once the heavy load time and the amount of load have been identified, the second sub-task is to determine the amount and position of the cluster head for the second-deployment to minimize the load. Meanwhile, the latency of ordinary nodes can reach a high level. This can be seen from the communication load in time T_{i+j}. There is a need to freshly deploy the two clusters head nodes in the grid 2 (g_2) when there is an increase in the number of mobile nodes. After the second-deployment of the cluster head nodes, the final step is to determine the sleep schedule of the cluster head nodes in the different grids. Here we assume that the load balance and the node movement change periodically and the time period T is of fixed length. We divide the time period into multiple sub-periods. These time periods are denoted by the sequence $t_0, t_1, t_2, \ldots, t_{nt}$. Our work is to find: a) a sleep mechanism at each key time t_i, which can be applied till the next key time t_{i+1}, and b) the set of sleep cluster head nodes.

We assume that each cluster head node has the same initial power P. We know that after some time, every CHN will have a different power level, and hence, it becomes challenging to select the appropriate CHN to put it into sleep mode. Given two grids g_1 and g_2, as shown in Fig. 3a, the challenge is to find the time and load amount of the heavy load time, and then second-deploy some CHN to these grids. In the final step, we identify the sleep schedules (CHN's start and end sleep time). In this way, the traffic load balance can achieve an acceptable performance, and the total energy consumption of the whole network is minimized.

B. CURRENT NETWORK FEATURE EXTRACTION FROM BIG DATA

We assume that there are N pieces of historical records. The networks current method for features extraction from big data is composed of two sub-algorithms: a) Creating Networks features Database (CNFDB) for different grids and times, and b) Search the Heavy Traffic Load Grids and Time period (SHTGT). It is obvious that their results are affected by the historical records of the networks and devices. The details are shown in Fig. 4 and 5.

The flowchart of the proposed method called CNFDB is shown in Fig.4. In this method, first, the historical records (HT) are initialized by reading the data from the data center. Next, in the iteration $i \leq N_{TH}$, the records are checked to ensure that they belong to the current time and grid. Next, the data are classified using SVM (Support Vector Machine) or other sorting methods (e.g. K-means) according to the time period and the grid. In the last step, the classified data are stored into the network features database (NB) for the next setup.

As shown in Fig. 5, the SHTGT stores a number of network features such as the different time periods and grids in the database of traffic load (L) called NB. Each iteration of the SHTGT algorithm identifies the value of L that exceeds the threshold (L_{TH}) of the grid and the corresponding time when this happens. During an iteration $j \leq N$, when L is greater than L_{TH}, the grid is identified and recorded. Next, using related methods (e.g. Quick Sort) we can identify the maximum traffic loads in different grids. Finally, these results are stored in the matrix (TL) with the grid identity and the corresponding time.

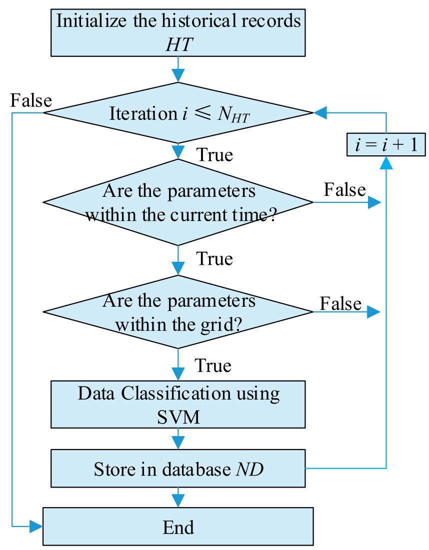

FIGURE 4. Proposed method Creating Networks Features Database.

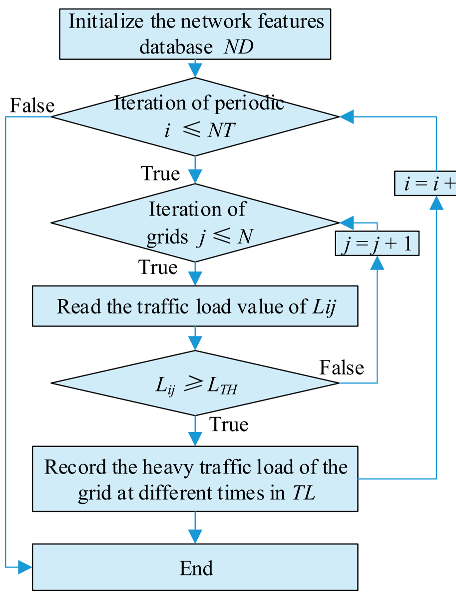

FIGURE 5. Steps of Search the Heavy Traffic Load Grids and Time period.

C. SECOND-DEPLOYMENT AND SLEEP SCHEDULING METHODOLOGY

Most previous research works have focused on deployment and sleep scheduling to maximize the lifespan of system. However, the previous studies have only considered a simple situation where a large number of ordinary nodes are placed at fixed positions with a fixed traffic load. The previous works do not allow dynamic changes to the traffic load. These assumptions run counter to the reality observed in wireless networks for big data. Hence, instead of using static positions and loads, this work proposes an effective method to second-deploy the cluster head nodes, and provide sleep

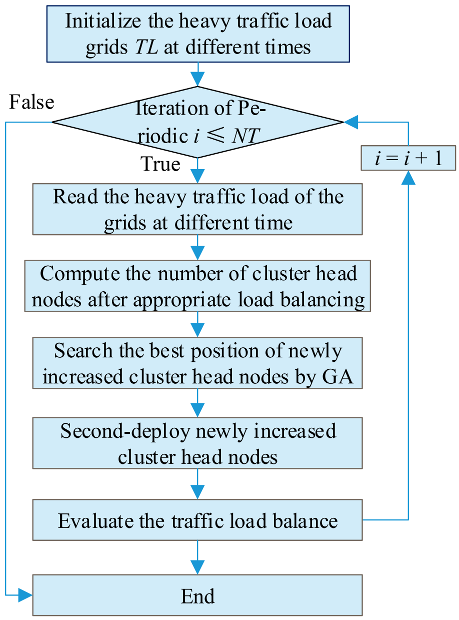

FIGURE 6. Flowchart of Second Deployed with an improving Genetic Algorithm.

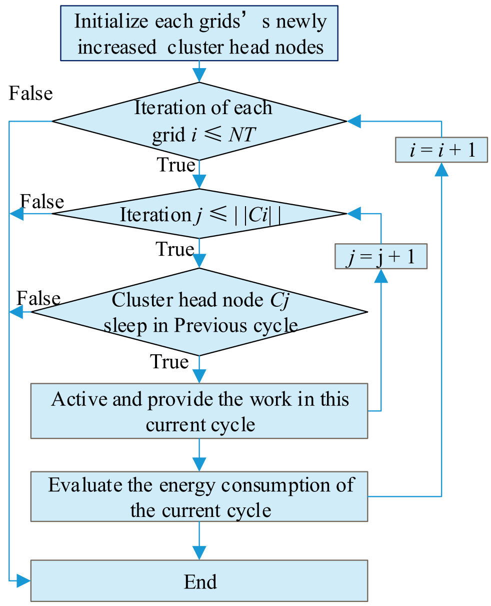

FIGURE 7. Steps of Alternate Sleep Scheduling.

scheduling for mobile networks and dynamic traffic load management.

Our work for second-deployment and sleep scheduling can be divided into two phases: first, some new cluster head nodes are second-deployed into the mapping grids using an improved genetic algorithm (SDGA). Next, according to the grid number and the time period, an alternate sleep scheduling (ALSS) is proposed. The flowchart of the proposed second-deployment and sleep scheduling is shown in Fig. 6 and 7. It is described in detail as follows.

The flowchart of the proposed method called SDGA is given in Fig. 6. Each iteration of the SDGA method second-deploys the cluster head nodes in each grid, based on the result of the SHTGT. The Fig. 6 shows the three stages of each iteration. Stage 1 iterates over the cluster head nodes in the heavy traffic load grid. Stage 2 searches the best position of the newly increased CHN using GA or some other heuristic algorithm. Finally, the newly populated CHNs are second-deployed at the appropriate computing position in stage 3. After the three stages are completed, the total load balance of the entire network is evaluated.

The ALSS method is demonstrated in Fig. 7. In the ALSS method, after second-deploying the newly populated CHNs, the system can achieve an optimal level balance. In this proposed method, we aim to minimize the energy consumption of the CHNs. To do this, the algorithm consists of two steps. For each iteration $i \leq NT$, when the traffic load decreases, the sleeping CHNs in each grid are identified. In the inner iteration, the sleeping CHNs are activated. Next the energy consumption is evaluated.

Application of these three methods to a wireless big data network can achieve a traffic balance and optimize the energy consumption. In a grid g_i, the maximized traffic load is identified and the newly populated CHNs number and deployment positions are computed. In the last step, to save energy, the sleep scheduling is restored according to the previous states.

V. SIMULATION AND RESULTS

In this section, we build the numerical simulation environments. The average communication loads of each grid and CHN, and the average residual energy obtained by our algorithm are compare with those obtained through traditional strategy.

A. SIMULATION SETTINGS

The simulation setting is described as follows. The simulation area A is represented as $A = 1000\text{m} * 1000\text{m}$; the transmission range of every node is 100m; the traffic load of each node is 10; the CHN can undertake a traffic load up to 100; that is, it can provide communication service to 10 nodes. The number of mobile nodes within the simulation area A is 500, 600, 700 and 800 respectively moving from left to right in the grid. The number of moving nodes is 1000 and they are evenly distributed in every grid. Additionally, the other parameters of the proposed method are set as follows. The initial battery power of each CHN is 1000. Every communication between the nodes consume a power of 0.1. The total number of grids is 10*10.

B. BASIC PERFORMANCE METRICS

The key contribution of the proposed method is second-deployment and sleep scheduling for the dynamic wireless big data network. Hence, we must analyze the traffic balance and energy consumption for the different number of

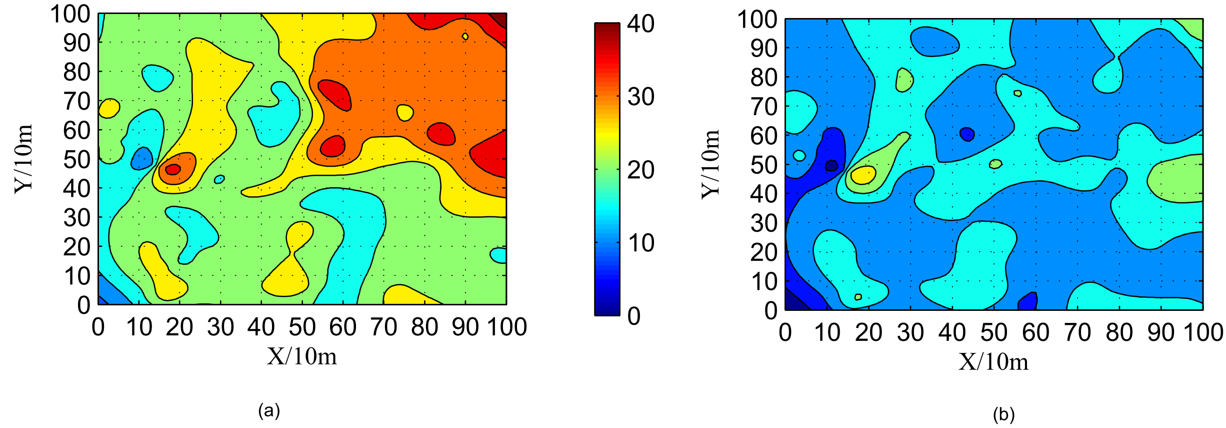

FIGURE 8. **Comparison of the traffic loads of every grid traffic for different methods. (a) the contour map of the traffic load with adopting traditional method; (b) the contour map of the traffic generated by using the SDSS method.**

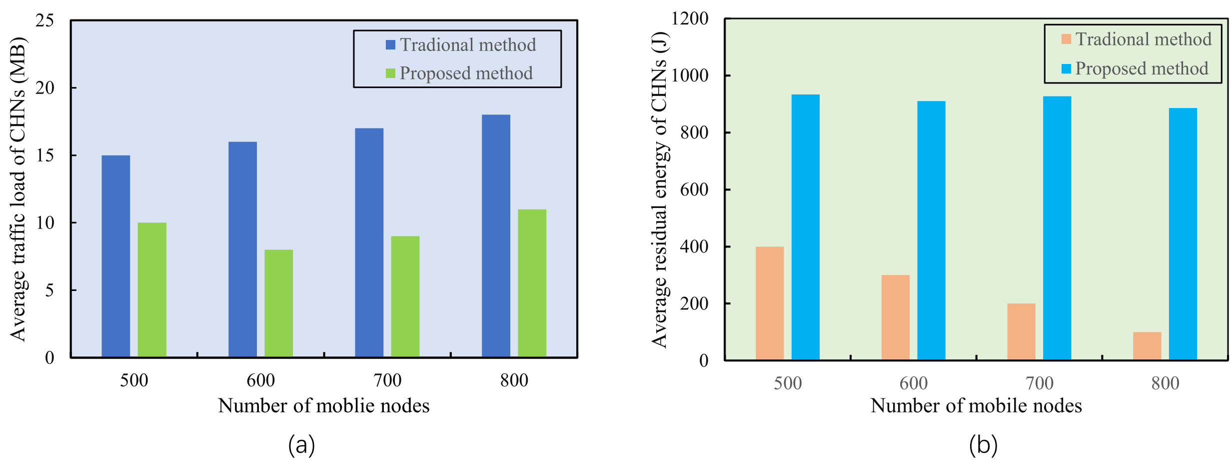

FIGURE 9. **Comparison of the average residual energy and the traffic load for the proposed and the traditional methods. (a) average traffic load of CHNs; (b) average residual energy of CHNs.**

nodes. As illustrated in Fig. 8 and Fig 9, every result represents an average value calculated through 100 simulation runs. In Fig. 8, we demonstrate the traffic load changes of the entire simulation area. Fig. 8(a) represents the contour map of the traffic load in every grid at a certain moment before applying our proposed method. We can observe that all the values of traffic load are greater than 10. The traffic load in the upper right corner of the Fig. 8(a) is greater than 25, due to the movement of the mobile nodes. Within the range of $x = 20$, $y = 40$, there is a hot area consisting of heavy traffic because the static nodes there undergo changes in the communication task. From Fig. 8(a), it is easy to note that in an industrial wireless network, the traffic load is dynamic and may change with time. Fig. 8(b) is the contour map of the traffic generated while using the SDSS method. From this figure, we can conclude that application of our proposed method can lead to a reduction in the traffic load. Moreover, the traffic load for every grid is less than 20. Comparing with the Fig. 8(a), we see that in Fig. 8(b) there is no hot area. Thus, we demonstrate that our proposed method can better handle dynamic traffic load change.

From Fig. 9, we can observe that our proposed method with joint consideration always has a better performance in all cases. When the number of nodes increases, the performance difference becomes greater. From Fig. 9(a), we can observe that the average residual energy (ARE) of the traditional method gradually decreases with an increase in the number of mobile nodes in the system. However, for our proposed method, the ARE remains unchanged with an increase in the number of the mobile nodes. Therefore, we can conclude that our proposed method will have a longer lifespan than the traditional one. In Fig. 9(b), we can see the result of the average traffic load (ATL) of CHNs. We know that the traditional methods ATL will increase with the number of the mobile nodes. In contrast, in our proposed method the value of ATL is always less than 15. Namely, our proposed method will always have a lower ATL and a higher real-time factor than the traditional method. Therefore, our proposed method provides significant advantages in terms of ARE and ATL, which are important evaluation indictors for wireless big data networks. Therefore, our proposed method is more suitable for applications in industry 4.0 smart factories.

VI. CONCLUSION

The greatest challenges of wireless networks for big data in the context of a smart factory are a) mobile nodes and b) dynamically changing heavy traffic load. These can cause imbalances in traffic and energy consumptions of cluster head nodes in hierarchical networks. In this article, we introduced a methodology for incorporating deployment and sleep scheduling of such nodes in an industry 4.0 factory. Due to the movement of the mobile nodes, the traffic load of each grid will change dynamically with time. By analyzing the historical records of traffic load for each grid using an industrial big data strategy, network features can be extracted and the peak in traffic and the corresponding time can be identified. Using a distributed genetic algorithm to obtain an optimal traffic balance level, we second-deploy the cluster head nodes. At last, based on the service time model, we propose a novel sleep-wake scheduling method. Simulation results demonstrate that the proposed method performs better than traditional methods, and the performance advantages increase with an increase in the number of nodes. Aside from obtaining a good balance and effective communication, the proposed method is also able to decrease the network latency.

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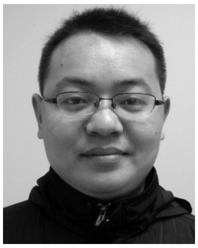

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