A Task Scheduling Strategy in Heterogeneous Multi-sinks Wireless Sensor Networks

Liang Dai
School of Electronic and Control Engineering, Chang'an University, Xi'an 710064, China
Email: ldai1981@gmail.com

Hongke Xu
School of Electronic and Control Engineering, Chang'an University, Xi'an 710064, China
Email: xuhongke@chd.edu.cn

Ting Chen
School of Information Engineering, Chang'an University, Xi'an 710064, China
Email: tchenpcn@126.com

***Abstract*—Using multiple sinks in a wireless sensor network can significantly decrease the amount of energy spent on communication, so it has been paid much attention in recent years. In this paper, we introduce a new divisible load scheduling strategy to solve the problem how to complete the tasks within the possibly shortest time in multi-sinks wireless sensor network. In this strategy, the tasks are distributed to wireless sensor network based on the processing and communication capacity of each sensors by multiple sinks. After received the sub-tasks, the intra-cluster sensors perform its tasks simultaneously, and send its results to cluster head sequentially. By removing communications interference between each sensor, reduced makespan and improved network resource utilization achieved. Cluster heads send fused data to sinks sequentially after fused the data got from intra-cluster sensors, which could overlap the task-performing and communication phase much better. A unique scheduling strategy that allows one to obtain closed form solutions for the optimal finish time and load allocation for each node in heterogeneous clustered networks is presented. And solutions for an optimal allocation of fractions of task to sensors in the network are also obtained via bi-level programming. Finally, simulation results indicate this strategy reasonably distributes tasks to each node in multi-sinks wireless sensor networks, and effectively reduces the time-consuming of task completion. Compared to the traditional single-sink structure, makespan is reduced by 20%, and the energy-consuming of sensors is more balanced.**

***Index Terms*—wireless sensor networks, heterogeneous, divisible load theory, task scheduling, multiple sinks**

I. INTRODUCTION

In recent years, it's discovered that the stability and effectiveness of wireless sensor networks faced a huge threat if there is only one sink as data management center. In view of this situation, multi-sinks wireless sensor networks become a new hotspot [1-2]. As shown in Figure 1, Data acquisition in single-sink sensor networks might have issues in scalability. As the size of sensor networks grows, the distances between the sink and the responding sensors become larger. This leads to a greater energy consumption for query-flooding and data-collection between sensors and the sink, leading to a possible reduction in the lifetime of the sensors. Hence, we need to design energy-efficient data acquisition mechanisms that scale with the size of the network. One solution is to simultaneously deploy multiple sinks in the sensor network.

Owing to the wireless sensor network node with limited energy, the task should be completed within the shortest possible amount of time. Divisible load theory [3] provides an effective solution to wireless sensor networks for task scheduling [4-7]. Different from other heuristic solutions of task scheduling problem in wireless sensor networks [8-9], this scheme can get not only the optimal solution, but also the analytic solution, thus ensuring the consistency of the results of scheduling.

Divisible load scheduling algorithms were applied to wireless sensor networks in [4-7]. Although the authors derived closed-form solutions to obtain the optimal finish time, the network topology discussed in those papers is single-level tree structure. While in wireless sensor networks, as compared with the single-level tree structure, clustered structure (multi-level tree structure) has a great of advantages [10].

Therefore, we present a task scheduling algorithm(DMTA) based on divisible load theory in multi-sinks wireless sensor networks The goal of this algorithm is to minimize the overall execution time (hereafter called makespan) and fully utilize network resources, by finding an optimal strategy of splitting the original tasks received by sink into a number of sub-tasks as well as distributing these sub-tasks to the clusters in the right order, and through the proposed mechanism to encourage collaboration.

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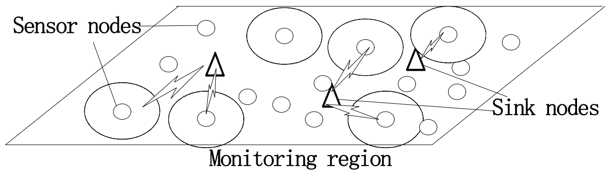


Figure1. Multi-sinks wireless sensor networks

II. Related works and our contributions

Due to the nature of distributed sensing in wireless sensor networks, it is expected that divisible load theory will play an important role in providing an optimal solution for load distribution under WSN environments, especially those having various energy and computational constraints. Divisible load theory was firstly applied to wireless sensor networks for the task scheduling analysis in [4]. The type of application this work involves measurements from a sample space where each sensor is assigned a certain nonoverlapping part of the sample space to measure. For instance, the sample space may consist of a very large frequency range and performing measurements by a single sensor may be both time and energy consuming. Although the authors derived closed-form solutions to obtain the optimal finish time for three particular sensor networks, their single level (single-hop) model is not scalable to a large sensor network. While in wireless sensor networks, as compared with the single-level tree structure, clustered structure (multi-level tree structure) has a great of advantages [10]. In [5], based on [4], Liu analyses the delay of measurement and communication in single-level wireless sensor networks. LIU applied divisible load theory to wireless sensor mesh networks to analysis task scheduling, the task issuing and the results reporting are also based on single-level tree [6]. Kijeung considers a single channel cluster composed of single cluster head and n sensors in the wireless network (star topology). This is a simple network scenario where the intra-cluster sensors can report their own sensory data directly to the clusterhead via a single channel. But in a hierarchical wireless sensor network, the network sensor nodes are usually partitioned into multiple clusters. Single cluster means very little in wireless sensor networks [7]. Existing research efforts on multi-cluster three tier hierarchical wireless sensor networks model based on four scenarios (single/multi channel, with/without front-end) [11-13]. However, the network models in those papers are assumed to be homogeneous.

To the best of our knowledge, no paper has given a satisfactory solution to the case where both the sensor network is heterogeneous and with multiple sinks, and measurement results transfer to the source is explicitly considered.

In this paper, the task scheduling problem of heterogeneous clustered wireless sensor networks with multiple sinks is formulated and analyzed in detail. The major contributions of this paper are: we present a task scheduling strategy in heterogeneous clustered wireless sensor networks with multiple sinks. The goal of this strategy is to minimize the overall execution time (hereafter called makespan) and fully utilize network resources, by finding an optimal strategy of splitting the original tasks received by sinks into a number of sub-tasks as well as distributing these sub-tasks to the clusters in the right order. The strategy consists of two phases: intra-cluster task scheduling and inter-cluster task scheduling. Intra-cluster task scheduling deals with allocating different fractions of sensing tasks among sensor nodes in each cluster; inter-cluster task scheduling involves the assignment of sensing tasks among all clusters. This strategy builds from eliminating transmission collisions and idle gaps between two successive data transmissions. By removing performance degradation caused by communication interference and idles, the reduced finish time and improved network resource utilization can be achieved. With the proposed strategy, the optimal finish time and the most reasonable load allocation ratio on each node could be derived.

In wireless sensor networks, cluster head is responsible for data exchange for SINK and in-cluster nodes. In order to reduce energy consumption caused by transmitting redundant data, lower latency and prolong the survival period, cluster head needs fuse the data [14]. A new estimation method for data fusion — information utilization constant is introduced[7] in this paper. Information utilization constant is based on a technique of information accuracy estimation. Through estimating accuracy of information, cluster head can know the approximate percentage of data fusion.

III. Problem description

Wireless sensor networks construct clusters several times in its life cycle. Each cluster will have a set-up phase and a steady-state phase. We discuss our task scheduling strategy in a steady-phase phase.

The original tasks received by sinks are divided into two stages: inter-cluster task scheduling and intra-cluster task scheduling. First, inter-cluster task scheduling partitions the entire tasks into each cluster, and then the sub-tasks in a cluster is assigned to each intra-cluster sensor nodes by intra-cluster task scheduling.

According to divisible load theory, to remove performance degradation caused by communications interference, sinks sends each round's tasks to cluster head sequentially. After each cluster finishing its tasks and fusing the data, the cluster heads also send this round's results to sinks sequentially. That in every moment only allows sinks node sends sub-tasks to a cluster head, or a cluster head return fusion data to the sinks.

Divisible load theory is characterized by the fine granularity of loads. There is also no precedence relation among the data elements. Such a load may be arbitrarily partitioned and distributed among sensors and links in a system. So without loss of generality, we use double–sinks wireless sensor networks as model to analyze the task scheduling problem in multi-sinks wireless sensor networks.

The network topology discussed in this paper is shown in Fig. 2.

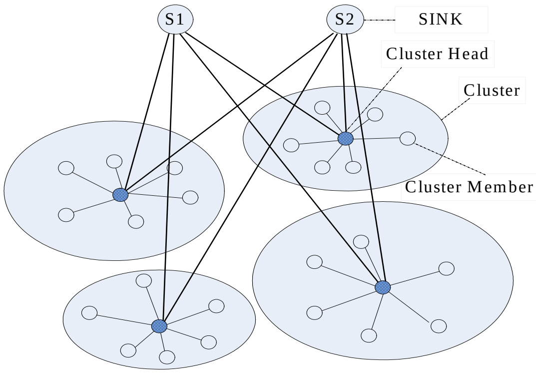


Figure2. Network topology

There are two sinks (S_1 and S_2) and k clusters ($Cluster_i$, $i=1,....,k$) in the network. Each cluster head were expressed as Ch_i , $i=1,....,k$. Within $Cluster_i$, there are n_i , $i=1,....,k$ nodes expressed as n_{ij} $(i=1,....k; j=1,...n_i)$ respectively. Communication links between Cluster head and the two sinks are expressed as l_{1i} and l_{2i} , $i=1,....,k$ respectively. Communication links between intra-cluster nodes and cluster heads are expressed as l_{ij} $(i=1,....k; j=1,...n_i)$ respectively.

The following notations will be used throughout this paper:

L_s : Total load originated from sink s , $(s=1,2)$

α_i : The total fraction of load that is assigned by the sinks to cluster head i , $(i=1,....,k)$

α_{1i} : The fraction of load that is assigned to cluster head i by the first sink;

α_{2i} : The fraction of load that is assigned to cluster head i by the second sink;

$$\alpha_i = \alpha_{1i} + \alpha_{2i}, \ (i=1,....,k) \quad (1)$$

$\alpha_{1i,j}$: The fraction of load that is assigned to intra-cluster node n_{ij} in cluster i by the first sink;

$\alpha_{2i,j}$: The fraction of load that is assigned to intra-cluster node n_{ij} in cluster i by the second sink;

By definition we can see:

$$\sum_{i=1}^{k} \alpha_i = 1 \quad (2)$$

$$\sum_{j=1}^{n_i} \alpha_{1i,j} = \alpha_{1i} \quad (3)$$

$$\sum_{j=1}^{n_i} \alpha_{2i,j} = \alpha_{2i} \quad (4)$$

ω_i : A constant that is inversely proportional to the processing (data fusion) speed of cluster head Ch_i .

$y_{i,j}$: A constant that is inversely proportional to the measuring speed of intra-cluster node n_{ij} in the network.

z_{1i} : A constant that is inversely proportional to the speed of link between the first sink and the i th cluster head in the network

z_{2i} : A constant that is inversely proportional to the speed of link between the second sink and the i th cluster head in the network

$z_{i,j}$: A constant that is inversely proportional to the speed of link between the cluster head Ch_i in the network.

T_{ms} : Measurement intensity constant. This is the time it takes the intra-cluster node n_{ij} to measure the entire load when $y_{i,j}=1$. The entire assigned measurement load can be measured on the intra-cluster node n_{ij} in time $y_{i,j}T_{ms}$

T_{cm} : Communication intensity constant. This is the time it takes to transmit the entire processing load over a link when $z_i=1$. The entire load can be transmitted over the i th link in time z_iT_{cm}

T_{cp} : Data fusion intensity constant. This is the time it takes to fuse the entire load on a cluster head when $\omega_i=1$. The entire load can be fused on cluster head Ch_i in time $\omega_i T_{cp}$.

φ_i : The information utility constant of cluster head Ch_i .

The operation process of the entire application is as follows:

1. Sink firstly divided the general task and assigned the sub-tasks to each cluster head.
2. Each cluster head partitioned the tasks it received then distributed to the nodes within its cluster.
3. Intra-cluster nodes performed measurement while reported the results to the cluster head.
4. Cluster head fused the data it received from intra-cluster nodes while sent the fused data to the sink node.

IV. Optimal Scheduling Algorithm

Wireless sensor networks construct clusters several times in its life cycle. Each cluster will have a set-up phase and a steady-state phase. We discuss our multi-rounds task scheduling algorithm in a steady-phase phase.

The original tasks received by sink are divided into two stages: inter-cluster task scheduling and intra-cluster task scheduling. First, inter-cluster task scheduling partitions the entire tasks into each cluster, and then the sub-tasks in a cluster is assigned to each intra-cluster sensor node by intra-cluster task scheduling. To improve overlap of communication with computation, inter-cluster task scheduling assigned sensing tasks among all clusters in multiple rounds.

According to divisible load theory, to remove performance degradation caused by communications interference, sinks sends tasks to cluster head sequentially. After each cluster finishing its tasks and fusing the data, the cluster heads also send this round's results to SINK sequentially. That in every moment only allows SINK node sends sub-tasks to a cluster head, or a cluster head return fusion data to the sinks.

Two generic techniques for solving linear divisible load schedule problems are linear equation solution and linear programming. Analytical closed form solutions have the advantage of giving insight into system dependencies and tradeoffs. Furthermore, analytical solutions, when they can be realized, usually require only a trivial amount of calculation. Linear programming has the advantage of being able to handle a wide variety of constraints and producing numerical solutions for all types of linear models. Alternately one can often, though not always, set up a set of linear equations that can be solved either numerically or, in special cases, analytically.

In this subsection A, a typical closed form solution for task scheduling of heterogeneous wireless sensor networks is achieved. In subsection B, a representative task scheduling problem with bi-level programming solution is discussed.

A. A closed form solution

A.1 **Intra-cluster task scheduling**

Fig.3 illustrates the timing diagram for a set of sensor nodes, indexed from n_1 to n_k, in one cluster. From Fig.3, it can be observed that there is no time gap between every two successive nodes because the divisible workload can be transferred in the cluster. All sensor nodes start to measure data at the same time. Once the previous node finishes transmitting data, the other one completes its measuring task and starts to report its data. As a result, the proposed timing diagram minimizes the finish time by scheduling the measuring time and reporting time of each senor node. Moreover, since the intra-cluster scheduling tries to avoid the transmission conflicts at the cluster head, energy spent on retransmission are conserved.

The working time of a sensor node can be divided into two parts: measuring time and reporting time.

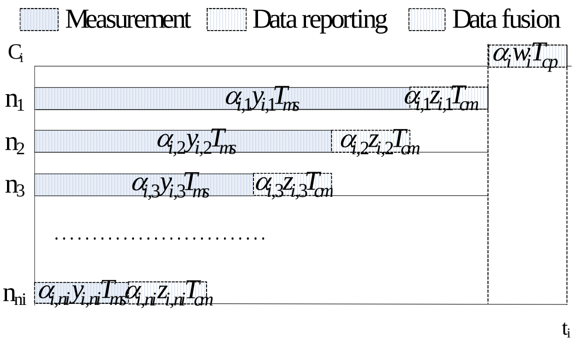


Figure 3. Timing diagram for intra-cluster task-processing

The task scheduling model considered in this paper is shown in Figure 3. The intra-cluster nodes began collecting data at the same time, and report the results collected to cluster head.

In order to fully utilize the link bandwidth, and avoid the waiting between different nodes, intra-cluster nodes completed reporting data collected to cluster head synchronously. Cluster head received the reported data from intra-cluster nodes, then fused those data, and sent the fused results to sink.

Similarly, in order to remove the performance degradation caused by idle, and to improve efficiency, cluster head completed reporting the fused data to the sink node.

For Cluster head C_i, based on the timing diagram shown in Fig. 3, one can write the following set of equations:

$$\alpha_{1i,j-1} y_{i,j-1} T_{ms} = \alpha_{1i,j} y_{i,j} T_{ms} + \alpha_{1i,j} z_{i,j} T_{cm}, \quad i = 2, 3, \ldots k \tag{5}$$

A general expression for the above set of recursive equations can be written as

$$\alpha_{1i,j} = s_{i,j} \alpha_{1i,j-1} \tag{6}$$

where $s_{i,j} = y_{i,j-1} T_{ms} / (y_{i,j} T_{ms} + z_{i,j} T_{cm})$ and $i = 2, 3, \ldots k$

The above recursive equation for $\alpha_{1i,1}$ can be rewritten in terms of α_{1i} only as

$$\alpha_{1i,1} = \alpha_{1i} / (1 + \sum_{j=2}^{n_i} \prod_{k=2}^{j} s_{i,k}) \tag{7}$$

The cluster head will use the above value of $\alpha_{1i,1}$ to obtain the amount of data that has to be measured by the rest of the $n_i - 1$ sensors by using

$$\alpha_{1i,j} = \alpha_{1i} \prod_{k=2}^{j} (s_{i,k}) / (1 + \sum_{j=2}^{n_i} \prod_{k=2}^{j} s_{i,k}) \tag{8}$$

The minimum measuring and reporting time of the first sink's sub-task α_{1i} will then be given as

$$t_{1i} = \alpha_{1i} (y_{i,1} T_{ms} + z_{i,1} T_{cm}) / (1 + \sum_{j=2}^{n_i} \prod_{k=2}^{j} s_{i,k}) + \alpha_{1i} w_i T_{cp} \tag{9}$$

Similarly we can get the minimum measuring and reporting time of the second sink's sub-task α_{2i} is :

$$t_{2i} = \alpha_{2i} (y_{i,1} T_{ms} + z_{i,1} T_{cm}) / (1 + \sum_{j=2}^{n_i} \prod_{k=2}^{j} s_{i,k}) + \alpha_{2i} w_i T_{cp} \tag{10}$$

A.2 **Inter-cluster task scheduling**

After cluster heads fused the cluster's measured data, cluster heads can sent the fused data to sinks concurrently because each cluster head has a separate channel to the sinks.

In order to remove the performance degradation caused by idle, and to improve efficiency, as shown in Fig. 4, we can get

$$\varphi_i \alpha_{2i} z_{2i} T_{cm} = t_{2i} + \varphi_i \alpha_{1i} z_{1i} T_{cm} \tag{11}$$

In eq. (11) and (12), we make

$$(y_{i,1}T_{ms} + z_{i,1}T_{cm}) / (1 + \sum_{j=2}^{n_i} \prod_{k=2}^{j} s_{i,k}) + w_i T_{cp} = s_i$$

, then take s_i to eq. (13), we can get

$$\alpha_{1i} = r_i \alpha_{2i} \tag{12}$$

where $r_i = \varphi_i z_{2i} T_{cm} / (s_i + \varphi_i z_{1i} T_{cm})$

The total tasks cluster head Ch_i get is :

$$\alpha_i = \alpha_{1i} + \alpha_{2i} \tag{13}$$

From Fig. 4 one can see that:

$$\alpha_i s_i + \varphi_i \alpha_{1i} z_{1i} T_{cm} = \alpha_{i+1} s_{i+1} + \varphi_{i+1} \alpha_{1,i+1} z_{1,i+1}{}^1 T_{cm} \tag{14}$$

From eq. (14) to eq. (16), we can get

$$\alpha_i l_i = \alpha_{i+1} l_{i+1} \tag{15}$$

where $l_i = s_i + r_i \varphi_i z_i{}^1 T_{cm} / (1 + r_i)$

Now using the eq. (1), one can solve for α_i as

$$\alpha_i = (1/l_i) / \sum_{i=1}^{k} (1/l_i) \tag{16}$$

Hereto, we can get that the tasks cluster head Ch_i and the intra-cluster nodes within it received from the first sink $\alpha_i{}^1$ and $\alpha_{i,j}{}^1$. Similarly, the tasks from the second sink $\alpha_i{}^2$ and $\alpha_{i,j}{}^2$. And the total task execution time

$$T_f = t_{2i} + t_{1i} + \varphi_i \alpha_{1i} z_{1i} T_{cm} \tag{17}$$

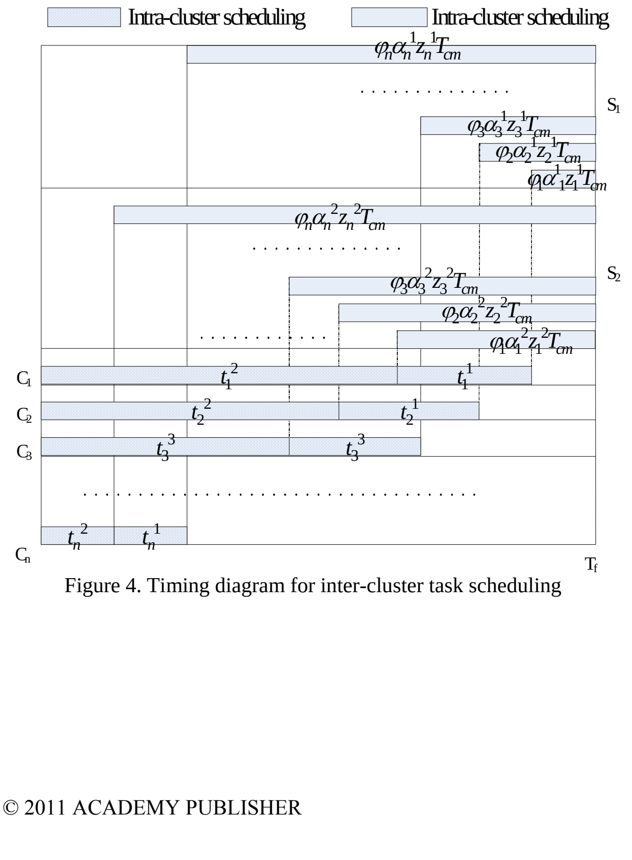


Figure 4. Timing diagram for inter-cluster task scheduling

B. A bi-level programming method

In this subsection, a bi-level programming model is constructed in the task scheduling problem of wireless sensor networks.

We can regard the task scheduling problem as a Leader-Follower problem.

The upper-level can be described as the load allocation ratio of sinks allocated to each cluster head satisfying the divisible load theory, which make the makespan minimum. The lower-level can be described as the load allocation ratio of cluster head allocated to each intra-cluster sensor divisible load theory, which make the intra-cluster task completion times minimum.

The problem of minimizing the total task finish time in scheduling algorithm is described below:

$$t_{2i} + t_{1i} + \varphi_i \alpha_{1i} z_{1i} T_{cm} \le T_f \tag{18}$$

So, for the upper-level programming, the mathematical model is as follow:

$$Min\ T_f$$

$$subject\ to\ (Cluster\ head\ C_i)$$

$$t_{2i} + t_{1i} + \varphi_i \alpha_{1i} z_{1i} T_{cm} \le T_f,\ i = 1, \dots, k \tag{19}$$

$$\sum_{i=1}^{k} \alpha_i = 1,\ \alpha_i \ge 0,\ i = 1, \dots, k$$

When the upper-level programming achieves optimal, the most reasonable load allocation ratio α_i on each cluster head could be derived. According to the load allocation ratio α_i on each cluster head, the optimal load allocation ratio $\alpha_{i,j}$ on each intra-cluster sensor can be determined by the lower-level programming.

For the lower-level programming, the mathematical model is as follow:

$$Min\ \ t_i\ \ i = 1, \dots, k$$

$$subject\ to\ (Sensor\ S_{i,j})$$

$$\sum_{k=1}^{j} \alpha_{i,k} z_{i,k} T_{cm} + \alpha_{i,j} y_{i,j} T_{ms} \le t_i,\ j = 1, \dots, n_i \tag{20}$$

$$\sum_{j=1}^{n_i} \alpha_{i,j} = \alpha_i,\ \alpha_{i,j} \ge 0,\ j = 1, \dots, n_i$$

From the above, a bi-level programming model is constructed in the synthetic Problems of task scheduling for wireless sensor networks. The most reasonable load allocation ratio α_i on each cluster head could be fixed by the upper-level programming, and the lower-level programming established the most suitable load allocation ratio $\alpha_{i,j}$ on each intra-cluster sensor. In the above programming, α_i and T_f are the target function and the decision variable of upper level respectively, and

$\alpha_{i,j}$ and t_i are the target function and the decision variable of lower level respectively.

On minimum makespan T_f as the target function, the most reasonable load allocation ratio α_i on each cluster head as the decision variable, the programs to realize the optimization hauling project of minimum expenses and to output various forms are compiled according to the demand.

V. WIRELESS ENERGY USE

In this section, the energy model of the OTSA-WSN algorithm is presented in detail and the equations of energy consumption of individual sensor nodes are derived. The model is based on first-order radio model [10].

There are three kinds of energy consumption in the wireless sensor network: measurement, data fusion, and communication. Because nodes in the sensor networks cooperate with each other via data transmission, energy consumption of communications exists in sensor nodes, cluster heads and sink. It is not necessary for cluster heads and sinks to perform any sensing task. Thus, there is no energy cost for cluster heads due to the measurement of these nodes, while the additional energy cost of cluster heads attributes to data fusion. The energy to sense, fuses, and transmits a unit sensory data are denoted by e_s, e_p and e_{tx}, respectively. Sensor nodes also consume the energy of e_{rx} to receive one unit of data. The distance between the sender and the receiver is d.

The energy use for each kind of nodes is outlined as follows:

Energy use for individual sensor nodes j in cluster i:

$$E_{i,j} = \alpha_{i,j}(e_s + e_{tx}d^2), i = 1,\cdots,k, j = 1,\cdots,n_i \tag{21}$$

Energy use for individual cluster head:

$$E_i = \alpha_i(e_{rx} + e_p + \varphi_i e_{tx}d^2), \ i = 1,\cdots,k \tag{22}$$

Energy use for sink:

$$E_{SINK} = \sum_{i=1}^{k} \alpha_i \varphi_i e_{tx} \tag{23}$$

VI. PERFORMANCE EVALUATION

In this section, we investigate the effects of different measurement/communication speed under homogeneous network environment on the total task finish time (makespan) and energy consumption of every intra-cluster nodes, and compare the 2-sinks model to the traditional single sink structure.

In the simulation, the following energy parameters are adopted: transmitting a unit of sensor reading over a unit distance takes e_{tx}=200nJ, receiving one unit of sensor reading consumes e_{rx}=150nJ, measuring one unit of sensor reading needs e_s=100nJ, fusing one unit of observation consumes e_p=20nJ and the distance between the sender and the receiver is d=100m. There are 30 sensor nodes in each cluster.

The simulation results are shown in Figure 5 to Figure 7.

Firstly, the makespann against the number of clusters are plotted in Fig. 4. In Fig. 4(a), the value of measurement speed is chosen from 0.8 to 1.6, while communication speed is fixed to 1.0. This figure shows that measurement speed almost does not affect the makespan because sensing takes a small fraction of the entire execution time. Fig. 4(b) shows that when the communication speed of nodes increases, the makespan of a given task is reduced. It can be found that the five lines in Fig. 4(b) converge when the number of clusters becomes large.

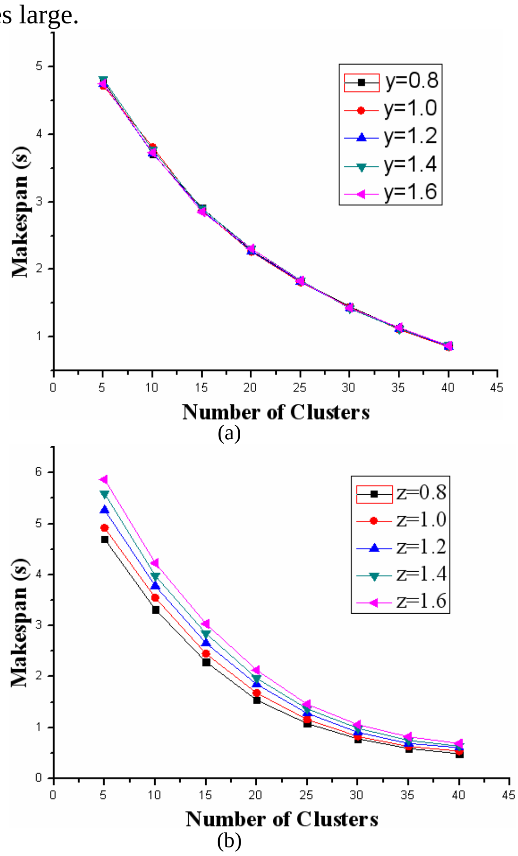
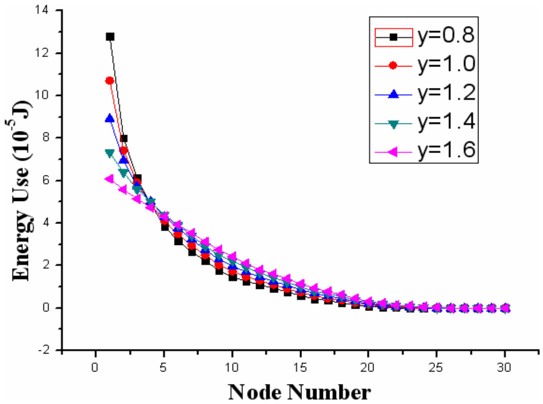
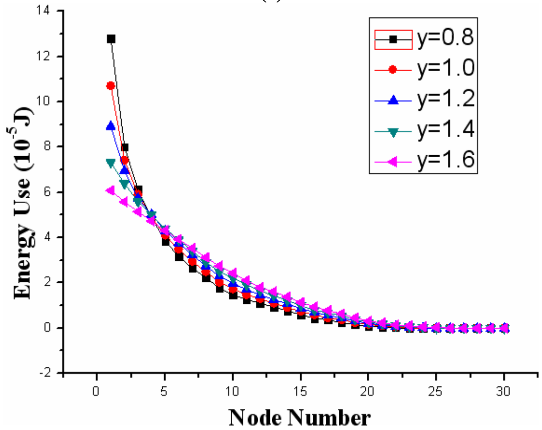


Figure 5. Impact of measuring speed and bandwidth on the makespan

Next, the second simulation is about the energy consumption of intra-cluster nodes. Sinks and cluster heads are not taken into account because generally, sinks has no energy constraint and the chosen cluster heads have the possibly enough energy. The network is configured with 20 clusters. Without loss of generality, the intra-cluster nodes in the first cluster are chosen to study the energy consumption, as shown in Fig.5. Fig. 5(a) shows the higher the intra-cluster node's measuring speed, the more evenly the tasks allocated to each nodes, hence the smaller the energy consumption of the nodes. Fig. 5(b) presents the larger communication speed between senders and receivers, the smaller the energy consumption of the intra-cluster nodes.



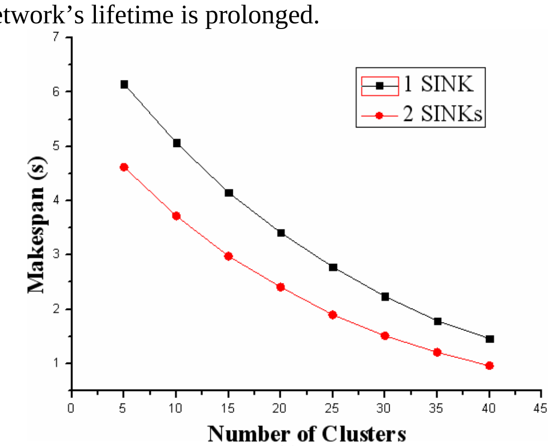
(a)



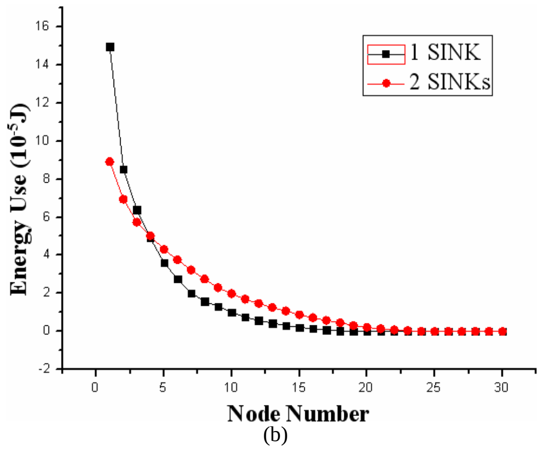
(b)

Figure 6. The impact of measuring speed and bandwidth on the energy consumption in intra-cluster nodes

Then, Fig.6 reflects the comparison of time-consuming and energy-consuming of two network architecture in dealing with the same task. In the simulation, we supposed that: $y=z=w=1.0$. As can be seen from Fig. 6(a), the task completion time is reduced by 20% in network with 2 sinks due to better computation and communication overlap. Fig. 6(b) shows that the energy-consuming of sensors is more balanced, so the network's lifetime is prolonged.



(a)



(b)

Figure 7. Comparison of time-consuming and energy-consuming of the two network architecture

VII. CONCLUSIONS

As the nodes in wireless sensor network have limited energy, so the tasks should be completed as soon as possible. In this paper, we present a new task scheduling strategy in heterogeneous clustered wireless sensor networks with multiple sinks based divisible load theory, to solve the problem how to complete the tasks within the possibly shortest time. In this strategy, the tasks are distributed to wireless sensor network based on the processing and communication capacity of each sensors by multiple sinks. After received the sub-tasks, the intra-cluster sensors perform its tasks simultaneously, and send its results to cluster head sequentially. By removing communications interference between each sensor, reduced makespan and improved network resource utilization achieved. Cluster heads send fused data to sinks sequentially after fused the data got from intra-cluster sensors, which could overlap the task-performing and communication phase much better. The strategy consists of two phases: intra-cluster task scheduling and inter-cluster task scheduling. Intra-cluster task scheduling deals with allocating different fractions of sensing tasks among sensor nodes in each cluster; inter-cluster task scheduling involves the assignment of sensing tasks among all clusters. Solutions for an optimal allocation of fraction of task to sensors in heterogeneous wireless sensor networks are obtained via closed-form solution and bi-level programming solution, respectively.

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Liang Dai was born in 1981. He was graduated from Xidian University with Ph. D in Communication and Information System in 2011. He is with Chang’an University from 2011.

His research interests include wireless sensor networks and digital signal processing in mobile communication.

Hongke Xu received the B.Sc. degree in traffic control and management from Chang'an University, Xi’an, China, in 1985, the M.Sc. degrees in computer engineering from Xidian University, Xi’an, in 1993, and the Ph.D. in traffic control and management from Chang'an University.

He is currently a Professor with the School of Electronic and Control Engineering, Chang'an University. His major research interests are in the fields of traffic control and management, and ITS.

Ting Chen was born in 1982. She was graduated from Xidian University with Ph. D in Communication and Information System in 2011. She is with Chang’an University from 2011. Her research interests include wireless communication networks, corss-layer design, QoS guarantee mechanism, and etc..