Topology-Aware Energy Efficient Task Assignment for Collaborative In-Network Processing in Distributed Sensor Systems

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Abstract In the emerging networked sensor systems, collaborative in-network processing provides a viable solution to overcome the limited energy and resource constraints of one single node. In this novel computing paradigm, it is very critical to perform task assignment. In this paper, we formally model TETA, an energy efficient topology-aware real time task assignment problem in wireless sensor networks, and prove its NP-completeness. We also propose an ant-based meta-heuristic algorithm to solve the TETA problem. We implement our algorithm and conduct experiments based on a simulation environment. The experimental results show that our approach can archive significant energy saving and improve the system lifetime effectively as well.

1 Introduction

With recent technological advances in sensing, computing, communication and wireless networking, distributed sensor systems are increasing deployed owing to their wide popularity of applications. In these systems, collaborative in-network data processing techniques have been proven to be an effective way to significantly reduce energy consumption. In this novel collaborative computing paradigm, applications are partitioned into tasks that are executed in a distributed manner. To meet the application requirements, these tasks should be assigned to different sensor nodes.

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Hence, the task assignment problem is a fundamental issue and plays a critical role in the collaborative data processing.

Task assignment is a classical problem in the traditional computation paradigm. However, in distributed sensor systems, several distinct issues, such as energy efficiency,node location, network topology, should be particularly addressed. For instance, in high-performance computing and grid computing, there are many assignment techniques focused on interconnect or wired networks. In these models, processing units are either fully connected via interconnect or wired networks [3, 12], or some special topology such as chains[9], trees[2], 2D-mesh, 3D-Torus[10],etc.These topologies are different from those in wireless environments.

Recently,localized task assignment problem has been investigated in wireless sensor networks. In [4], Heemin et al. presented a simulated annealing framework for energy-efficient task assignment and migration in sensor networks. An Integer Linear Programming model is introduced by Yang and Viktor in [11], they also proposed a three-phase heuristic named EbTA. In [7], An algorithm named EcoMapS is proposed for jointly mapping and scheduling tasks in single-hop cluster. In [6], Yuan presented RT-Maps which can provide a real time guarantee. All the above techniques concentrate on task assignment in one hop. In practice, multi-hop collaboration is more popular in wireless sensor networks.

Latest studies have been conducted to multi-hop environments. In [5], Yuan et al. proposed a multi-hop collaborative in-network processing algorithm. However, network topology is not considered in their work. In wireless sensor networks, topology is a fundamental issue and should be taken into consideration.The approaches ignoring the location and topology of sensors may not work correctly.

In this paper, we focus on topology aware energy efficient task assignment problem in wireless sensor networks. To our best, this is a first attempt to deal with the task assignment problem in multi-hop sensor networks considering the underlying network topology. Our main contributions are summarized as follows:

- We study and address the topology-aware energy efficient task assignment problem for multi-hop sensor networks. We formally model TETA, an integrated model for both reducing the system-level energy consumption and providing real-time guarantee. We also prove its NP-completeness.
- We propose ANT-TETA, an ant based meta-heuristic algorithm to solve the TETA problem. Through multiple artificial ants travels the network and assign the tasks sequentially, this heuristic approach can exploit the underlying topology more better, and provides a good solution for TETA. Also, it can be easily extended to work in a decentralized and parallel way.
- We have implemented this work in a simulation environment, and compare it with the extension of existing approaches. The experimental results show that our approach can achieve significant energy saving and improve the system lifetime.

The rest of this paper is organized as follows.In section 2, we introduce the topology-aware energy efficient task assignment problem. Based on some system level assumptions, the formal definition of TETA is given. The proof of its NP-completeness is presented in section 3. We then propose the ANT-TETA algorithm in section 4. We provide the experiments results and analysis in section 5. Finally, the conclusion is given in section 6.

2 Problem Statement

In this section, we first introduce some realistic assumptions. Based on these assumptions, we formally define the application model, network model and energy model. Thereafter, the formal problem statement is given.

- System Assumptions

We assume the following system assumptions:

1. A sensor network consists of heterogeneous nodes. Each sensor node is equipped with a computing unit,sensors and a wireless module. Nearby nodes form a logical multi-hop computation environment called cluster. Applications are executed inside the cluster in a collaborative manner.
2. We adopt the collision free model[10]. The link collision can be avoided by link scheduling approaches.
3. The network topology information is available for sensor nodes inside the cluster.

- Application Model

In distributed and parallel computing, applications are modeled as DAG graphs. We assume the target application can be represented by $TG = (V_T, E_T, V_{ET}, vw, ew, TC)$. V_T denotes all the computational tasks,and vw represents tasks' computational overhead. E_T consists of communication edges between associated tasks,and ew is the function of communication throughput on the edges. In sensor applications, the entry tasks are always from special sensor nodes. The set of entry tasks is denoted as V_{ET}. The overall timing constraint is assumed to be TC.

- Network Model

The network topology is always modeled as a connected graph $NG = (V_G, E_G, cc, dw)$. V_G is the set of sensor nodes,E_G is the set of communication edges.To enhance the network lifetime,each sensor node can only perform limited computation,and this limitation is modeled as cc. The communication distance between two nodes is modeled as function dw.

- Energy Model

We adopt the same energy consumption model as [8].

$$P_{cpu} = \alpha C_L * V^2 * f + I_{leak} * f \tag{1}$$

$$P_{TX}(d) = E_{elec} + \varepsilon_{amp} d^{\partial} \tag{2}$$

$$P_{RX} = E_{elec} \tag{3}$$

In the CPU power model,α,C_L and I_{leak} are processor dependent parameters,V and f denote the working voltage and frequency,respectively.The transmitting and receiving power of the wireless module are shown in equation 2 and 3. E_{elec} and ε_{amp} are electronic parameters, d is the transmitting distance, and $2 \leq \partial \leq 4$. In our experiments, we adopt the parameters of μAMPS[8].

- Task Assignment

In general, the goal of task assignment is to assign tasks to sensor nodes. Assume m represents the assignment result.That is, task T_i is assigned to a sensor node $m(T_i)$.After the assignment is done, the communication edge is mapped to the shortest path between nodes. In a specified assignment m, we assume $E^{(m)}_{comp}(T_i)$ denotes the energy consumption of task T_i, $E^{(m)}_{comm}(e_{ij})$ denotes the energy consumption of communication edge e_{ij}, and $L(m)$ is the finish time of application.

- Problem Definition

Given task graph and network topology, the objective of task assignment is :

Minimize:

$$E^{(m)}_{total} = \sum_{t_i \in V_T} E^{(m)}_{comp}(t_i) + \sum_{e_{i,j} \in E_T} E^{(m)}_{comm}(e_{i,j}) \tag{4}$$

Subject to:

$$L(m) \leq TC \tag{5}$$

3 Problem Complexity

In this section, we prove that the TETA problem is NP-complete by a reduction from the subgraph isomorphism problem.

Definition 1. the TATAS_DP problem:

Given a positive number K, TC, a task graph TG, a network topology NG, an assignment m, is the total energy consumption K, and the total execution time for the task graph TG $L(m) \leq TC$?

Definition 2. Sub Graph Isomorphism problem:[1]

Given two graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$, G_1 is isomorphic to G_2 if there is a function f which maps the vertices of G_1 to vertices of G_2 such that for all pairs of vertices x, y in V_1, edge (x, y) is in E_1 if and only if the edge $(f(x), f(y))$ is in E_2.

Theorem 1. *the decision problem of the TATAS problem is NP-complete.*

Proof: Since we can check $E^{(m)}_{total}$ and $L(m)$ using equations (1-5), and this process can be finished in polynomial time, The TATAS_DP problem belongs to NP.

Assume $I =< G1, G2, f >$ is an instance of sub graph isomorphism, where $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$, f is a mapping function from G_1 to G_2. We will construct a TATAS_DP problem instance from I.

Let a vertex d be any node in V_1, A task graph $TG = (V_1, E_1, \{d\}, vw, ew)$ is constructed from G_1 directly. The function vw and ew is configured to assign and for each node and edge G_1, respectively. A network topology $NG = (V_2, E_2, dw)$ from G_2.For each edge $e_{i,j}$ in E_2, $dw(e_{i,j}) = 1$.

We assume the total computation energy consumption as E_{comp}. We set TC to infinite and set K as

$$K = E_{comp} + e_{comm} * (2 * E_{elec} + \varepsilon_{amp}) * |E_1| \tag{6}$$

The mapping function $f^{'}$ from TG to NG can be constructed from f in polynomial time by:

$$\forall v \in V_1, f^{'}(v) = f(v) \tag{7}$$

$$\forall e_{i,j} = (v_i, v_j) \in E_1, f^{'}(e_{i,j}) = (f(v_i), f(v_j)) \tag{8}$$

We will prove that $f^{'}$ is a feasible solution to the TATAS_DP problem if and only if f is a solution to sub graph isomorphism decision problem I.

Suppose f is a solution to sub graph isomorphism decision problem I. In $I^{'}$, the total energy consumption of mapping $f^{'}$ will be

$$\begin{aligned} E_{total} &= E_{comp} + \sum_{e_{i,j} \in E_1} E(e_{i,j}) \\ &= E_{comp} + e_{comm} * (2 * E_{elec} + \varepsilon_{amp}) * |E_1| \leq K \end{aligned} \tag{9}$$

Thus, $f^{'}$ is a feasible solution to $I^{'}$.

On the contrary, if a solution $f^{'}$ for $I^{'}$ is found, we can also prove f is a feasible solution by reduction to absurdity. If any edge in the task graph is mapped to a path with more than one edge, then the energy consumption in this communication will be larger than $e_{comm} * (2 * E_{elec} + \varepsilon_{amp})$. Therefore, the total energy consumption will be:

$$\begin{aligned} E_{total} &= E_{comp} + e_{comm} * (2 * E_{elec} + \varepsilon_{amp}) \sum_{e \in E_1} p(e) \\ &\geq E_{comp} + e_{comm} * (2 * E_{elec} + \varepsilon_{amp}) * |E_1| = K \end{aligned} \tag{10}$$

It violates the assumption that $f^{'}$ is a valid solution to $I^{'}$. So the TETA problem is NP-complete.

4 The Proposed ANT-TETA Algorithm

Since the TETA problem is NP-complete, heuristic approaches can be proposed. Inspired by the efficiency of ant colony optimization in solving graph-related problems, we propose an ant based task assignment algorithm named ANT-TETA. In this section, we first introduce an overview of ANT-TETA, and then describe its key components in section 4.2.

4.1 Overview

The overview of the ANT-TETA algorithm is shown in Fig.1.

```
   Input: Task Graph TG, Network Topology Graph NG
   Output: assignment from TG to NG.
1  Initialize the pheromone matrix and other data structures.;
2  foreach ant k do
3  |   ant k build its task list L(k) via topological sorting using Depth-First Search;
4  end
5  while terminate condition is not meet do
6  |   foreach ant k do
7  |   |   L = L(k);
8  |   |   while L is not empty do
9  |   |   |   Pick out the next unassigned task i from L in sequential order;
10 |   |   |   Build the candidate node set CS(i);
11 |   |   |   For each node j in CS(i), calculate its probability through heuristics and
   |   |   |   pheromone;
12 |   |   |   Select node j stochastically according to its probability;
13 |   |   |   Assign task i to node j, update the assignment information and other
   |   |   |   information such as node capacity;
14 |   |   end
15 |   end
16 |   update the pheromone matrix;
17 |   update other statistics information;
18 end
19 Output the final solution;
```

Fig. 1 The ANTS-TETA algorithm

We assume the number of entry tasks is q. ANT-TETA tries to obtain a better assignment through the collaboration of q artificial ants. In step (2-4), each ant k will build a list $L(k)$ by topological sorting the task graph from its corresponding entry task nodes. $L(k)$ determines the task assignment order of ant i in step(8-12). From step (5), ANT-TETA performs task assignment in a standard ant system manner. In step (6-15), ant k assigns tasks to sensor nodes one by one following the sequential order of $L(k)$.Since the assignment of ants executes independently, this can be done in a distributed and parallel manner. After all the ants finish its assignment, the pheromone matrix and other information is updated as in step16-17. Since this process is based on the well known ant system, we will only focus on some critical steps in the next subsection.

4.2 Key Components

- Heuristic desirability

Heuristic desirability η_{ij} implies the fitness function of assign task i to node j. In ANT-TETA,let E_{ij} and $E_{ij}^{(total)}$ denotes increase and total energy consumption if task i is assigned to node j, and L_i denotes the application execution time after task i is assigned to node j,the heuristic desirability is defined as

$$\eta_{ij} = \begin{cases} \lambda \frac{E_{ij}}{E_{ij}^{(total)}} + \mu \frac{L_i}{TC} & \text{if } L_i \leq TC \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where λ and μ is application specific parameters.

- Building candidate set

In step (10),let $rc(N_j)$ denotes the remain computation capacity in node N_j, ant k will construct a candidate node set $CS_{T_i}^{(k)}$ based on the computation requirements:

$$CS_{T_i}^{(k)} = \{N_j | rc(N_j) \geq cc(T_i)\} \tag{12}$$

- Probability of assignment

In step (11), it plays a critical role in calculating assignment probability. Let p_{ij}^k denotes the probability of ant k assigns task i on node j is given by

$$p_{ij}^k(t) = \frac{\sum_{l \in CS_{T_i}^{(k)}} [\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta} \tag{13}$$

Where t is the iteration number,and α, β determines the weight given to the heuristic information and pheromone, respectively.

- Update the pheromone information

In step(16), when all the ants find a solution, the pheromone matrix will be updated with

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta \tau_{ij}^k \tag{14}$$

, where ρ represents the pheromone evaporation,$\Delta\tau_{ij}^{k}$ is the amount of pheromone ant k deposits on the assignment (i, j):

$$\Delta\tau_{ij} = \begin{cases} Q/E_k^{total} & \text{if } i \text{ is assigned to } j \text{ by ant } k \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

where E_k^{total} denotes the final energy consumption of assignment solution by ant k, and Q is a system parameter and it is application specific.

5 Simulation Results

We evaluate our ANT-TETA algorithm through simulations. In this section, we first introduce our simulation platform and parameters. Thereafter,we compare the results of our ANTS-TETA algorithm with the multi-hop extension of DCA[8]. Experimental results show that our algorithm can archive significant energy savings and improve the system lifetime.

5.1 Simulation Platform and Parameters

In order to evaluate the performance of the proposed algorithm, we build a simulation platform. As illustrated in Fig 2. This platform consists of three parts: DAG regulator, network topology generator(NTG),and assignment algorithms module.

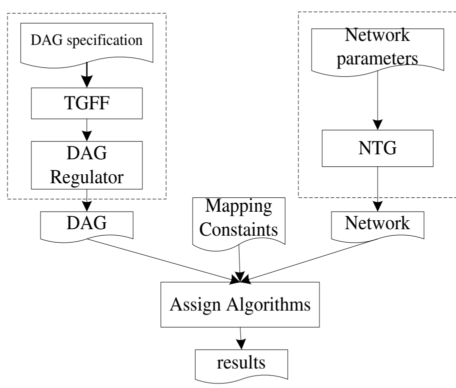

Fig. 2 The simulation platform

The DAG regulator is based on the **TGFF** tool. We use **TGFF** to generate DAG task graph,and regulate the results to meet the application requirements.In our experiments, we set the number of entry tasks to be 8, and set the maximum in degree and out degree to be 3 and 5,respectively. The computation workload and communication throughput are randomly chosen within the range of (100KCC, 600KCC) and (500bits, 1000bits). The raw sensing data is larger and is randomly chosen in the range of (4kbits, 8kbits).The computation workload and communication throughput are randomly chosen within the range of (100KCC, 600KCC) and (500bits, 1000bits),and its battery capacity is set to 1000Amh.

NTG is used to generate a random network topology. It assumes that the sink node is placed in the center of a 1km*1km area. It starts with placing specified number of randomly generated nodes within the area. Afterwards, it checks the connectivity. The nodes with a connectivity degree of zero is regarded as faulty nodes and will be replaced with new random nodes.This process continues until the node amount can meet the requirements.The computation capability of each node is selected within the range of (500KCC, 800KCC).

5.2 Results and Analysis

We compare our algorithm with the multi-hop extension of DCA. DCA represents the traditional and popular way of data processing. It executes the entry tasks on the corresponding sensing node, transmits raw data to the cluster head, and processes all the other tasks on the cluster head. We extend DCA with multi-hop support by constructing communication paths from entry sensors to the cluster head.

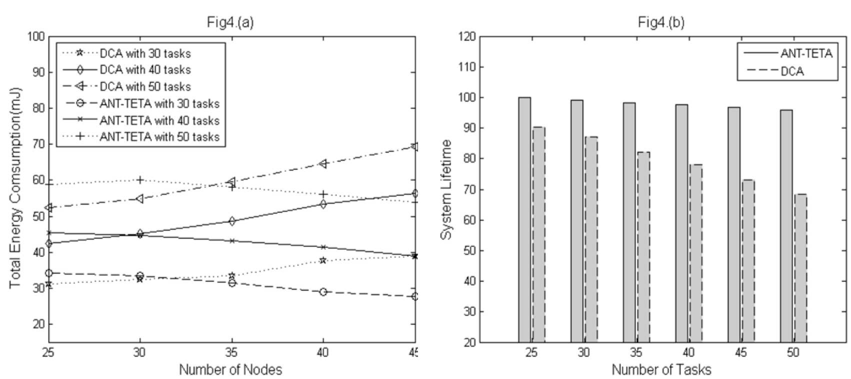

Fig. 3 The comparison between ANT_TETA and DCA

As shown in Fig 3, we compare ANT-TETA with DCA in terms of total energy consumption. With the number of nodes increases, the total energy consumption of DCA increases. Since DCA execute most tasks on the cluster head, its energy consumption depends on the communication activities. Thus, the change of network topology will influence it slightly. In contrast, the ANT-TETA is able to reduce its total energy consumption effectively for the underlying network topology.

The lifetime of sensor network is defined as the time after the first node runs out its battery.Compared with DCA, Our ANT-TETA can archive at most 28.9% improvements for the network lifetime. The reason is that DCA assigns too many tasks on the cluster head, which will exhaust the energy of the cluster head. What's more, this result comes from computation dominated applications. If the communication overhead is high, it will be more worse. Besides, in DCA, due to the huge size of raw sensed data, the other nodes in the transmitting path consume more energy. The result also indicates that the task assignment techniques of collaborative in-network processing are able to enhance the network lifetime dramatically.

6 Conclusion

In this paper, we formally define TETA, an energy efficient topology-aware real time task assignment problem in distributed sensor systems, and proved its NP-completeness. An ant-based meta-heuristic algorithm named ANT-TETA is proposed to solve the TETA problem. We also implement our algorithm in a simulation environment and conduct experiments. The experimental results show that our approach can archive significant energy saving and improve the system lifetime effectively as well.

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