

ENERGY AWARE MODEL FOR SENSOR NETWORK: A NATURE INSPIRED ALGORITHM APPROACH

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ABSTRACT

In this paper we are proposing to develop energy aware model for sensor network. In our approach, first we used DBSCAN clustering technique to exploit the spatiotemporal correlation among the sensors, then we identified subset of sensors called representative sensors which represent the entire network state. And finally we used nature inspired algorithms such as Ant Colony Optimization, Bees Colony Optimization, and Simulated Annealing to find the optimal transmission path for data transmission. We have conducted our experiment on publicly available Intel Berkeley Research Lab dataset and the experimental results shows that consumption of energy can be reduced.

KEYWORDS

Ant Colony Optimization, Bees Colony Optimization, Data Mining, DBSCAN, Sensor Network, Simulated Annealing.

1. INTRODUCTION

Sensor networks are deployed in the real world to acquire measurements at distinct points. The acquisition measurement by a sensor node is characterized specifically by two dimensions namely time and location. Recent developments in technologies have developed smart devices characterized by sensing, computational, and communication capabilities. These smart devices have been exploited in various applications such as traffic monitoring [1], surveillance [2], habitat monitoring [3], fire detection, pollution monitoring, and environmental monitoring etc for monitoring the given area continuously. To effectively accomplish this task, the acquisition of data from all the sensor nodes describing the state of the monitored environment is performed [1], [4-5]. Since the main cause for consumption of energy of sensor node are data acquisition and communication [6], these approaches are considered as highly energy consuming. Hence, smart and intelligent techniques are required to reduce the consumption of energy in sensor nodes by focusing the development of energy aware models during the data acquisition.

This paper describes the framework for the development of energy aware model for sensor network by minimizing the communication cost. Density based clustering technique such as Density Based Spatial Clustering of Applications with Noise (DBSCAN) is used to exploit the temporal correlation among the sensor data and spatial correlation among the sensor nodes. Among the correlated sensor data, a subset of sensor nodes is identified. Instead of querying all sensor nodes, only subset of sensor nodes is queried to reduce the amount of data to be acquired and transferred. To minimize the communication cost, travelling salesmen problem solver is used [7]. Experiments were performed on the publicly available Intel Berkeley Research lab dataset [8] to show the effectiveness of the proposed model.

The rest of the paper is planned as follows. Section 2 gives the literature survey; Section 3 describes the proposed model. Section 4 explains the experimental results and conclusion is given in Section 5.

2. LITERATURE SURVEY

Many researchers have devoted their precious time to develop the techniques for the better power management of sensor network. These techniques can be classified into three classes: (i) Reducing the number of transmission, (ii) reducing the number of sensor nodes required to answer the queries, (iii) identification of correlated sensors by exploiting the clustering techniques.

To detain the correlations and statistical relationships among the collected sensor attributes, a probabilistic approach was proposed in [9]. In this, a pull based approach is used to reduce the communication cost. But, in case of anomaly events, this approach does not respond in time. Based on the spatial and temporal correlations, a probabilistic model is proposed in [10]. In this approach communication is reduced by querying the network is only when sensors sense the values outside the error bound. By exploiting the forecasting the time series, a Probabilistic Adaptable Query (PAQ) system was proposed in [11]. In this model each node consists of a local probabilistic model whose parameters are notified to the base station. The base station uses all the local probabilistic models to predict the readings of each sensor nodes. When a sensor sense the reading which is not expected, it relearning phase is executed to build new model and the new model's information is sent to the base station.

To reduce the number of sensor nodes to be queried by selecting a subset of sensor nodes which represents the entire network state was first proposed by [12]. Sensor nodes exchange messages between their spatially correlated neighbours to select the representative sensors of their environment. This technique has been improvised in [13] by exploiting the temporal correlation among the sensor readings. But these techniques fail to identify the correlation among the sensors deployed far away.

Clustering techniques such as PREMON [14], LEACH [15], and CAG [16] have been exploited for the identification of subset of sensor nodes. In PREMON, MPEG compression algorithms are exploited in the cluster head node to predict the readings. Energy consumption is reduced by not transmitting the predicted data. In LEACH, randomized rotation of cluster heads ensures the energy overhead among the sensor nodes in the network. Given a spatial correlation threshold, CAG discovers the cluster of nodes by analyzing the sensed data. As long as the readings are within the threshold, only one reading per cluster is transmitted resulting in reduction in the amount of data acquiring and approximation of aggregation of results within in the threshold. However, these clustering techniques have their own limitations such as prior knowledge of clustering topology is required in PREMON, correlation among far away sensors cannot be detected in LEACH, and only one reading per cluster is transmitted in CAG.

3. PROPOSED MODEL

The proposed model consists of three phases. In the first phase, clustering technique is used to exploit the spatial and temporal correlation among the sensors. In the second phase, subset of sensor nodes is identified for each cluster. And in third phase, optimal transmission path is calculated for the data transmission using nature inspired algorithms such as Ant Colony Optimization (ACO), Bees Colony Optimization (BCO), and Simulated Annealing (SA).

3.1. Spatiotemporal relational model

Spatiotemporal relation model is one which identifies the correlation among the sensors in both spatial and temporal dimensions. For this it exploits the clustering technique. In particular, Density Based Spatial Clustering of Applications with Noise (DBSCAN). DBSCAN is selected over the partition based clustering techniques because DBSCAN can identify the spherical and non-spherical shaped clusters, it is less sensitive in presence of outliers, and it does not require to specify the number of clusters to be formed in advance. Once the DBSCAN is applied, outliers are identified and removed if there is any. The detailed description of DBSCAN algorithm is given in [17].

3.2. Identification of Representative Sensor Nodes

Identification of subset of sensor nodes plays a very important role in reducing the consumption of energy in sensor network. In this paper we have used the same technique as used in [18-19] for the identification of representative sensor nodes. Once we identify the subset of sensor nodes called representative sensors, instead of acquiring and transmitting data from all nodes only representative sensor nodes are used for acquiring and transmitting the data which results in reduction in the consumption of energy.

3.3. Optimal Transmission Path for Data Transmission

In a large sensor network data is transmitted to the base station through multiple hops. If the signal strength between any two sensor nodes is weak then packet may get lost resulting in retransmission of data which further increases the energy consumption. Hence, it is very important to identify the path whose signal strength is more compared to the other paths. But finding the optimal transmission path among all possible paths is a combinatorial problem which is very time consuming. Nature inspired algorithms such as Ant Colony Optimization (ACO), Bees Colony Optimization, and Simulated Annealing (SA) have been used in the past for solving combinatorial problems. In this paper we also used these nature inspired algorithms to identify the optimal transmission path for data transmission. The detailed description of nature inspired algorithms can be found in [20]

3.3.1. Ant Colony Optimization

Ant Colony Optimization technique was introduced by [21-22]. ACO is inspired by the behaviour of ants in the real world. In the real world, ant looks for the food and when food is found they return to their home. While returning to their home they lay the pheromone along the path. As the path is used more, more pheromone is collected along the path. And soon other ants also start following the same path. Soon or later all the ants will be travelling between the food source and their home on an optimal path.

In ACO, the pheromone and problem specific heuristic information is used to construct the probabilistic solution. For a given component i , the probabilistic solution is given by

$$P_{ij} \leftarrow \frac{\tau_{i,j}^{\alpha} \times \eta_{i,j}^{\beta}}{\sum_{k=1}^c \tau_{i,k}^{\alpha} \times \eta_{i,k}^{\beta}} \quad (1)$$

Where β is the heuristic coefficient, α is the pheromone coefficient, $\tau_{i,j}$ is the pheromone value, $\eta_{i,j}$ is the maximizing contribution to the overall score, and c is the set of utilizable components.

For each solution, local pheromone is updated using the following equation.

$$\tau_{i,j} \leftarrow (1 - \sigma) \times \tau_{i,j} + \sigma \times \tau_{i,j}^0 \quad (2)$$

Where σ is the pheromone factor, $\tau_{i,j}^0$ is the initial pheromone, and $\tau_{i,j}$ is the pheromone for the graph edge (i, j) .

Using the best candidate solution at the end of each iteration, pheromone is updated and decayed using the following equation.

$$\tau_{i,j} \leftarrow (1 - \rho) \times \tau_{i,j} + \rho \times \Delta_{\tau_{i,j}} \quad (3)$$

Where $\Delta_{\tau_{i,j}}$ represents the maximizing cost for the best solution if the component i, j known otherwise it is 0, ρ represents the decay factor, and $\tau_{i,j}$ represents the pheromone for the graph edge (i, j) .

3.3.2. Bees Colony Optimization

Bees Colony Optimization algorithm is inspired by the behaviour of bees in the real world. There are two types of bees namely scout bees and worker bees. Scout bees are sent to find out to search for the flower patches. On returning to hive, scouts communicate the information with the worker bees about the location and quality of the food source via a wangle dance. Then some of the scout bees return to the flower patch along with the worker bees and some scout bees go in search of new flower patches. And every time returning from the food source they communicate the quality of the food source.

The behaviour of bees is simulated to deal with the real world combinatorial problems. The basic idea of Bees Colony Optimization algorithm is to locate the good sites and explore them within the problem search space. Scouts are used to sample the problem search space and locate the good sites. These good sites are exploited using the local search where small number of good sites is explored compared to other sites. The pseudo code for the Bees Colony Optimization is given as follows.

Input: Problem_size, Bees_no, Sites_no, Elite_Sites_no, Patch_Size_init, Elite_Bees_no, Other_Bees_no

Output: Bee_best

Population \leftarrow *Initialize_Population(Bees_no, Problem_size)*
while(*Stop_Condition*)

Evaluate_Population(Population)

Bee_best \leftarrow *Get_Best_solution(Population)*

Next_Generation \leftarrow ()

Patch_size \leftarrow (*Patch_size* * *Patch_Decrease_factor*)

Sites_best \leftarrow *Select_Best_Sites(Population, Sites_no)*

foreach *Sites_i* \in *Sites_best* *do*

Recruited_Bees_no \leftarrow ()

If (*i* < *Elite_Sites_no*)

Recruited_Bees_no \leftarrow *Elite_Sites_no*

Else

Recruited_Bees_no \leftarrow *Other_Bees_no*

End If

Neighbourhood \leftarrow ()

For *j* *to* *Recruited_Bees_no* *do*

Neighbourhood \leftarrow *Create_Neighbourhood_Bee(Sites_i, Patch_size)*

End For

Next_Generation \leftarrow *Get_Best_Solution(Neighbourhood)*

End foreach

```

    Remaining_Bees_no ← (Bees_no – Sites_no)
    For j to Remaining_Bees_no do
        Next_Generation ← Create_Random_Bee( )
    End For
    Population ← Next_Generation
End while
Return Bee_best

```

3.3.3.Simulated Annealing

Simulated Annealing is a global optimization technique which belongs to the field of Metaheuristic and Stochastic optimization. It is mainly used for function optimization and is an adaptation of Metropolis-Hastings Monte Carlo algorithm.

Simulated Annealing inspired by the annealing process of metallurgy. To increase the strength and durability of the material, first the material is heated so that atoms of the material can move freely and then the material is cooled slowly under the controlled environment. This process increases the size of the crystals in the material and condenses their defects. The main objective of this mechanism is to locate the minimum cost configuration in the problem search space. The pseudo code for the Simulated Annealing is given as follows

Input: Problem_Size, Max_no_Iterations, Max_Temperature

Output: Best_Solution

```

Current_Solution ← Create_Initial_Solution(Problem_Size)
Best_Solution ← Current_Solution
For i=1 to Max_no_Iterations do
    Solution_i ← Create_Neighbour_Solution(Current_Solution)
    Current_Temperature ← Calculate_Temperature(i, Max_Temperature)
    If (Cost_Solution_i ≤ Cost_Current_Solution)
        Current_Solution ← Solution_i
        If (Cost_Solution_i ≤ Cost_Best_Solution)
            Best_Solution ← Solution_i
        End If
    Else If  $\text{Exp}\left(\frac{\text{Cost\_Current\_Solution} - \text{Cost\_Solution\_i}}{\text{Current\_Temperature}}\right) > \text{Random}()$ 
        Current_Solution ← Solution_i
    End If
End For
Return Best_Solution

```

4. EXPERIMENTAL RESULTS

We have implemented the proposed model using C#. We have used publicly available Intel Berkeley Research lab dataset [8] for the experiment purposes. This dataset consists of three tables namely location table, aggregate connectivity strength table, and sensor data. Location table contains the information about the physical location of each sensor node. Aggregate connectivity strength table contains information about signal strength between each pair of sensor nodes. And sensor data table consists of 2.3 million readings with attributes date and time, epoch, sensor id, temperature, humidity, light, voltage.

The proposed model consists of three main modules. (i) Spatiotemporal relation model identification of correlation among sensors in both spatial and temporal dimensions by exploiting

the DBSCAN algorithm. (ii) Selection of representative sensors. (iii) Finding the optimal transmission path data transmission using nature inspired algorithms namely Ant Colony Optimization, Bees Colony Optimization, and Simulated Annealing algorithm.

After applying DBSCAN, clusters were formed. Using the measurement strategy as explained in [18-19] we identified 23 sensor nodes as potential representative sensors. The figure 1 shows all the representative sensor nodes and the sensor nodes which they represent. The sensor nodes which are marked in a purple rectangle are the representative sensors and the boundary has been drawn if there is any sensor which is correlated to the representative sensor.

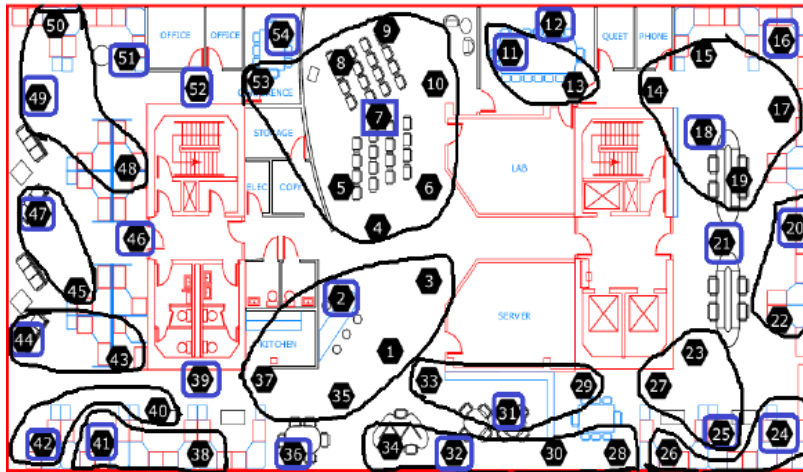


Figure 1 Representative Sensors

The optimal transmission path for data transmission is calculated using Ant Colony Optimization, Bees Colony Optimization, and Simulated Annealing algorithms. To calculate the best transmission path we have used the signal strength between each pair of sensor which is given in the aggregate connectivity strength table. The path is chosen as optimal path whose connectivity strength is higher compared to the other paths.

Table 1 gives the information about the parameters set in Ant Colony Optimization algorithm and figure 2 shows the output of the program. The optimal path found through the ACO is {47→2→12→42→46→52→31→20→25→24→49→39→41→36→54→11→18→21→16→51→7}

Table 1. Parameters of Ant Colony Optimization

Total number of ants used	10
Maximum execution time	1000
Pheromone influence α	4
Local node influence β	3
Pheromone evaporation coefficient (ρ)	0.05
Pheromone increase factor (Q)	1

```

C:\Windows\system32\cmd.exe
Begin Ant Colony Optimization demo
Number sensors in problem = 23
Number ants = 10
Maximum time = 1000
Alpha (pheromone influence) = 4
Beta (local node influence) = 3
Rho (pheromone evaporation coefficient) = 0.05
Q (pheromone deposit factor) = 1
Initializing dummy graph distances
Initializing ants to random trails
0: [ 44 46 39 21 . . . 31 32 51 24 ] len = 3.91743942464408
1: [ 44 52 36 39 . . . 41 47 20 51 ] len = 2.92241103371557
2: [ 12 31 46 42 . . . 36 21 2 11 ] len = 2.21771796953501
3: [ 42 47 16 46 . . . 25 7 51 36 ] len = 2.04605743158905
4: [ 47 2 12 42 . . . 21 16 51 7 ] len = 4.8
5: [ 2 49 12 24 . . . 31 20 41 7 ] len = 2.06965030228639
6: [ 41 44 39 20 . . . 18 32 12 46 ] len = 3.48609631527025
7: [ 42 21 12 36 . . . 47 46 49 16 ] len = 2.23994054716868
8: [ 54 46 24 32 . . . 49 2 41 44 ] len = 1.11794797027707
9: [ 20 21 47 18 . . . 51 2 41 12 ] len = 1.7896571557338

Best initial trail length: 4.8
Initializing pheromones on trails
Entering UpdateAnts - UpdatePheromones loop
Time complete
Best trail found:
Sensor Ids
47 2 12 42 46 44 52 31 20 25 24 49 39 41 36 32 54 11 18 21 16
51 7
Length of best trail found: 4.8
End Ant Colony Optimization
Press any key to continue . . .
    
```

Figure 2 Output of ACO

Table 2 Parameters of Bees Colony Optimization

Total number of inactive bees	25
Total number of active bees	50
Total number of scout bees	25
Maximum number of visits	100
Maximum number of cycles	3460

Table 2 gives the details of the various parameters set in Bees Colony Optimization algorithm and the obtained result is shown in figure 3. The optimal path found through BCO is {44→47→7→41→21→42→52→12→54→36→39→2→11→46→24→18→16→32→20→51→31→49→25}.

```

C:\Windows\system32\cmd.exe
Begin Bee Colony Optimization algorithm
Loading sensor nodes data
Cities: 2->7->11->12->16->18->20->21->24->25->31->32->36->39->41->42->44->46->47->49->51->52->54->
Number of sensor nodes = 23

Initializing the parameters of Bees Colony Optimizatoin algorithm

Total number inactive bees = 25
Number of active bees = 50
Number of scout bees = 25
Maximum number of visits = 100
Maximum number of cycles = 3460

Initial random hive
Best path found: 44->47->7->41->21->42->52->12->54->36->39->2->11->46->24->18->16->32->20->51->31->49->25->
Path quality: 13.7449

Entering algorithm main processing loop
Progress: !=====!
^^^^^^^^^^

Final hive
Best path found: 44->47->7->41->21->42->52->12->54->36->39->2->11->46->24->18->16->32->20->51->31->49->25->
Path quality: 13.7449

Press any key to continue . . .
    
```

Figure 3 Output of Bees Colony Optimization

Table 3 Parameters of Simulated Annealing

Maximum Temperature	1000
Delta distance	0
Cooling rate	0.9999
Absolute Temperature	0.00001

Table 3 gives the details of various parameters values set in our experiment and figure 4 shows the result obtained. The optimal path found by the Simulated Annealing algorithm is {2→7→12→11→16→18→21→20→24→25→31→52→49→41→36→51→44→46→47→42→39→32→54}.

```

C:\Windows\system32\cmd.exe
Initializing Simulated Annealing algorithm
Initializing the parameters of Simulated Annealing algorithm
Temperature: 10000
delta distance: 0
Cooling Rate: 0.9999
absolute Temperature: 1E-05
Strongest Route : 2 -> 7 -> 12 -> 11 -> 16 -> 18 -> 21 -> 20 -> 24 -> 25 -> 31 -> 52 -> 49 -> 41 -> 36 -> 51 -> 44 -> 46 -> 47 -> 42 -> 39 -> 32 -> 54
The strength of the connectivity is: 10.5636231907205
Press any key to continue . . .
    
```

Figure 4 Output of Simulated Annealing

5. CONCLUSIONS

Developing an energy efficient model for sensor network has been a major research challenge and various methodologies have been proposed in the past. In our proposed model we have exploited the DBSCAN clustering technique to explore the correlation among the sensors in both spatial and temporal dimension. Once the clusters are formed we identified the subset of sensor nodes which best represents the entire network state. We have identified 23 representative sensor nodes

which can be used to answer the queries instead of querying all 54 sensor nodes. This results in reduction in data acquiring and transmission of data by 57.40%. In the final stage we used nature inspired algorithms such as Ant Colony Optimization, Bees Colony Optimization, and Simulated Annealing techniques to find the optimal path for the data transmission. Finding an optimal path is necessary because if the path is not efficient or optimal then there is a possibility that data may not reach the destination successfully which result in retransmission of data causing more energy consumption. The optimal path increases the possibility of data being transmitted to the base station successfully. This results in decrease in the possibility of any packet being lost which results in reduction in consumption of energy.

The proposed model is best suited for static networks. In future we wish to address the key issue such as development of energy saving model for a dynamic sensor network.

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