PREDICTION BASED ENERGY AND DELAY AWARE DATA AGGREGATION FOR WIRELESS SENSOR NETWORKS

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ABSTRACT
Energy efficiency is a major issue in wireless sensor network (WSN) as sensor nodes are battery powered. By considering above issue, we propose prediction based energy and delay aware data aggregation technique in WSN. In the proposed technique, an efficient prediction model is constructed based on time series approximation method. Also suitable aggregator is selected based on the estimated one hop delay, Time to deadline and prediction error. This selection technique helps to choose reliable aggregator for data transmission without any delay. Then the data is transmitted by aggregator based on the waiting time which is calculated based on estimated one hop delay and residual energy to maintain energy efficiency in the network.

1. INTRODUCTION
1.1 WSN
Wireless Sensor Networks (WSN) is a collection of sensor devices and the connection between these devices are by means of wireless links. It accumulates the data that are processed in the distributed systems. The processed data can be obtained by means of the wireless connections. The employed sensor networks are capable of calculation, transmission and deposition. This network can be deployed in the harsh environments such as sensing the atmosphere, hospital management, construction and building supervision and military operation [1]. The sensor nodes that are deployed in the sensor network have the ability to accumulate the sensing information from the environment by means of continuous observation. These nodes operate collaboratively to transfer the accumulated data towards the base station or towards the destination sensor node. The chief benefit of this network is the infrastructure less network systems [2].

1.1 Issues of WSN
Sensor networks are application specific. One can’t have a solution that fits for all the problems. Sensor networks are data centric i.e. the queries in sensor network are addressed to nodes which have data satisfying some conditions and unique addressing is not possible as they do not have global identifiers [3].

The major issues that affect the design and performance of a wireless sensor network are as follows:
- Hardware and Operating System for WSN
- Wireless Radio Communication Characteristics
- Medium Access Schemes
- Deployment
- Localization
- Synchronization
- Calibration
- Network Layer
- Transport Layer
- Data Aggregation and Data Dissemination
- Database Centric and Querying
- Architecture
- Programming Models for Sensor Networks
- Middleware
- Quality of Service
- Security

1.2 Data Aggregation
The data aggregation algorithm is used to collect and accumulate the sensed information. It works in the way of effective utilization of energy. Hence the lifespan of the network can be increased.
The data gathering is the Systematic collection of sensed data from multiple sensors to be eventually transmitted to the base station for processing. The data gathering could be seen as a part of the data aggregation, if the function of this latter is divided into two parts. The first one is data gathering, which searches the close neighbor’s data (raw). The second part is the computation function, e.g computing the average value of the gathered data [4].

The classification of the data aggregation process is done by depending on the structure of the network, flow of the network, quality of services, etc. The data aggregation algorithm generally involves in data elicitation process and data accumulation process.

The data elicitation process can be defined simply as the operation of collecting the sensed data from the sensor nodes. The data accumulation process can be defined simply as the operation of evading the redundancy from the accumulated data. As a whole, the data aggregation process accumulates the data from the multiple neighborhood sensor nodes and they are transferred to the base station or the destination sensor node.

The structure based and the structure free is the two categories of the data aggregation process. The structure based data aggregation process has the classifications such as flat network based, cluster based, tree based and grid based [5]. The advantages of the data aggregation process are as follows. The data fusion process is used to minimize the redundant information which is available in the network. The redundant information may often available in the accumulated data of the sensor nodes. The other advantages include low traffic load, increased robustness, preservation of energy, and the enhanced accuracy of accumulated data.

Generally the de-centralized computation or the dynamic computation has disproportionate overhead in the transmission. Hence the structure based data aggregation process involves the centralized computation alone. Also the structure based data aggregation process is not suitable for the de-
centralized computation. This aggregation process is directly proportional to the waiting period in the intermediary sensor nodes. The waiting period may be either small or long. During the small waiting period, some of the accumulation process is performed. During the long waiting period, higher latency can be achieved. This waiting period can be calculated by means of the information about the position of the sensor nodes in the network [6]. Most of information dissemination proposals are focused on routing at layer 3; therefore, they do not have enough application contexts for filtering or in-network processing (e.g. routing assisted by application-specific code, in-network aggregation, data fusion, collaborative signal information processing. [7]

Data aggregation results in fewer transmissions, it potentially results in greater delays Therefore, in addition to transmission cost, the fusion cost can (and must) significantly affect routing decisions when data aggregation is involved. [8]

The data that are collected from the various sensor nodes are transferred to the cluster head. This cluster fuses the accumulated data and transferred to the base station. The cluster head can also be referred as the aggregator node. Since the data fusion process is concentrated in the cluster head node, it can be easily affected by the malicious attacks. The cluster head may be either compromised or uncompromised. The compromised cluster head does not guarantees the accurateness of the accumulated data. The uncompromised cluster head can results in the transmission of duplicate data to the destination sensor node or to the base station. This may results in the additional power consumption [9].

1.3. Problem Identification

From the existing works on structure based aggregation, it is analyzed that these works has discussed only small scale sensor networks and it need to suggest a scheme which is able to employ large scale. There is also need of improvement in accuracy and throughput. Efficient techniques are required for achieving spatial and temporal convergence in terms of selecting optimum node for aggregation and optimum time for waiting. In ARIMA (automatic auto regressive integrated moving average) model [17], a time-series prediction model is used to diminish the quantity of broadcasted values of the data among the sensor nodes and the cluster head. But it fails to discuss the spatial and temporal convergence properties for aggregation. In [15] and [18], structure-free Real-time Data Aggregation protocol (RAG) is developed considering the spatial and temporal convergence factors for aggregation. But it is mainly derived for structure free aggregation applied on event based sensors.

2. LITERATURE REVIEW

Atsushi Taked et al [10] have proposed a scalable structured p2p network which supports data aggregation. In p2p network each node forwards partial statistical results to other nodes and each node aggregates partial statistical results in order to calculate a complete statistical result, data aggregation process does not need any specific protocols, so the communication cost of the extension mechanism is very low. They simulate the proposed p2p network by using a p2p network simulator. Their simulation results indicate that the proposed data aggregation mechanism is effective enough.

Woo-Sung Hung et al [11] have proposed a hybrid clustering based data aggregation scheme. The proposed scheme can adaptively choose a suitable clustering technique depending on the status of the network, increasing the data aggregation efficiency as well as energy consumption and successful data transmission ratio. Their simulation results show the effectiveness of the scheme.

Chih-Min Chao et al [12] have proposed a protocol namely SFEB. This protocol is based on the structure free approach. It can also acts as the data aggregation process by effective utilization of the energy. This protocol can efficiently accumulate the data even in the two-phase aggregation process. Also it minimizes the consumption of energy by means of dynamic aggregator selection methodology. The simulator results are done by ns-2 to evaluate the performance of SFEB and SFEB-CL.

Jianghong Guo et al [13] have proposed a cluster trisecting based data aggregation scheme for wireless sensor networks in which the cluster was trisected and some reporters were assigned to each region. The nodes have same reading and located in same region with reporter will keep silent in data aggregating, thus reducing the inner-cluster transmissions. Their simulation show that the transmissions of inner-cluster aggregation in their scheme lower than that of related schemes and the decrease of transmissions is obvious when redundancy of sensor readings is high.

Cunqing Hua et al [14] have proposed an optimal routing and data aggregation scheme for wireless sensor network. The objective is to maximize the network lifetime by jointly optimizing the data aggregation and routing. They adopt a model to integrate data aggregation with the underlying routing scheme and present a smoothing approximation function for the optimization problem the necessary and sufficient conditions for achieving the optimality are derived and a distributed gradient algorithms is designed. Their simulation results reduce the data traffic and improve the network lifetime the distributed algorithm can converge to the optimal value efficiently under all network configurations.

Mohammad HosseinYenganeh et al [15] have proposed to make aggregation more efficient. They design novel structure-free Real-time Data Aggregation protocol, RDAG, using a Realtime Data-aware Routing policy and a Judiciary Waiting policy for spatial and temporal convergence of packets. Their simulations results done using ns-2 to verify the superiority of RADG in WSNs.

M.Y. Mohammed Yacoob et al [16] have proposed a cost effective compressive data gathering technique to enhance the traffic load, by using structured data aggregation scheme. We also design a technique that effectively reduces the computation and communication costs involved in the compressive data gathering process. The use of compressive data gathering process provides a compressed sensor reading to reduce global data traffic and distributes energy consumption evenly to prolong the network lifetime. Their simulation results show that their
technique improves the delivery ratio while reducing the energy and delay. Guorui Li et al [17] have proposed a scheme namely time series prediction scheme. It calculates the erroneous of the data by comparing this with the threshold limit of error defined by the application. The calculated values of data can be suitable for the real sensed values of data. In this scheme only very few messages are transferred in between the sensor nodes and the cluster heads. Thus the quantity of transferred values of data in between the sensor nodes and the cluster heads can be minimized. As a result, the battery power of the sensor nodes can be conserved. Hamed Youseif et al [18] have proposed on designing a structure-free Real-time data Aggregation protocol, RAG, using two mechanisms for temporal and spatial convergence of packets – Judiciously Waiting policy and Real-time Data-aware any casting policy. Using extensive simulations in NS-2, they show the performance of RAG in terms of aggregation gain, miss ratio, energy consumption, and end-to-end delay for WSNs.

3. PROPOSED SOLUTION

As a solution, we propose to develop a prediction based Data aggregation technique for wireless sensor network

In this solution, the each sensor node executes the ARIMA model for predicting the data values of sensors based on time series approximation [17]. After that it selects the aggregator or forwarder node based on its average residual energy, TTD (Time-To-Delay) and EHD (Estimated one-Hop Delay) [18] and send the predicted or sensed data after the waiting time. The waiting time for each sensor is decided by the factors estimated one-Hop Delay (EHD) [18] and ARIMA prediction error. The EHD depends on channel contentions, packet transmissions, and queuing delay.

3.2. Estimation of Metrics

This section describes about estimation of different metrics which is used in the proposed model:

3.2.1. Estimated One Hop Delay (Eohd)

It is defined as the amount of time taken to transmit data packet from one hop to another hop. It mainly depends on the factor such as packet transmission, channel condition and the queuing delay by using a time stamping technique.

3.2.2. Time To Deadline (TTD)

It determine the amount of time it remains for packet before its deadline and plays an important part while making routing decision.

3.2.3. Waiting Time (Wt)

It is the time after which the sensed and predicted data is sent to the sink which is I, hop away from the sink. It can be calculated as below:

\[
WT = \frac{TTD - EED}{1 + \left(\frac{I}{I_h} - 1\right)} \cdot \phi
\]  

(1)

\[
WT = \frac{TTD - (I_h \times EHOD)}{1 + \left(\frac{I}{I_h} - 1\right)} \cdot \phi
\]  

(2)

Here \( \phi \) represents constant factor which is used to leave some residual time as a margin to assure that deadline must be met.

EED represents estimated end to end delay. It is the time taken by the aggregator to deliver the packet to sink.

TTD-EED represents the Slack time which is proportional to the remaining hop count from the sink along the forwarding path to hold the packets in the intermediate node.

Also, the number of remaining hop count from sink can be given as below:

\[
I_h = \frac{D}{D_{Net}}
\]  

(3)

Where D represents the distance from current node to the sink node and to the next intermediate forwarding node.

3.2.4. Prediction Error (Eπ)

This metric is used to estimate the accuracy about the predicted data aggregation. It is calculated as below:

\[
E_\pi = S_i - P_i
\]  

(4)

Where \( S_i \) represents the sensed data and the \( P_i \) represents predicted data.

3.2.5. Residual Energy (E)π

It defines amount of energy left in the node even after maximum amount of energy is used for transmission. It is an important factor to make routing decision as node with the high residual energy can only be selected to transmit the data.

3.3. Data Value Prediction Model

The proposed data value prediction model is based on ARIMA [17]. It is mainly classified into three components:

- Auto Regressive (AR): It calculates the existing sample as a linear weighted sum of previous sample.
- Moving Average (MA): It helps to obtain relationship between prediction errors.
- One-step Differentiating: It helps to establish relationship between the adjacent samples.

The prediction Model \((x, y, z)\) of time series \((s_1, s_2, \ldots, s_n)\) is defined as below:

\[
\theta_s(D)\Delta^s\gamma s = \gamma_z(D)\eta_i
\]  

(5)

Where \( D \) represents backward shift operator, \( \Delta \) represents backward difference, \( \delta \) represents order of differencing, and \( \theta_s, \gamma_s \) represents polynomial of order \( x \) and \( y \) respectively.

\[
Ds_s = s_s - 1
\]  

(6)

\[
\Delta = 1 - D
\]  

(7)

The prediction Model ARIMA \((x, y, z)\) is the product of AR part AR \((x)\):

\[
\theta_x = 1 - \omega_1D - \omega_2D^2 - \ldots - \omega D^x
\]  

(8)

an integrating part

\[
H(y) = \Delta^{-y}
\]

and a MA part MA \((z)\):

\[
\gamma_z = 1 - \delta_1D - \delta_2D^2 - \ldots - \delta D^z
\]  

(9)

The parameter \( \theta \) and \( \gamma \) are elected so that zero of both polynomial lie outside the unit circle to prevent generation of unbounded processes.

The construction step of prediction model is explained as below:

Step 1: Make time series stationary through differencing technique

The noise series being considered must be static. In some cases the difference between the data present in...
the noise list will not be fixed. In order to make them fixed, the process of differencing is performed on the original data. As a result the data can be altered. In case the any series display a continuous trend over time or in case some other non-static pattern exist then the series is repeated till the stationary time series is achieved.

Step 2: Model Identification using autocorrelation function (ACF) and partial autocorrelation function (PACF).

If the series of time is turned to fixed then the identification process of nominee for the predicted model begins. The numerous prediction models which are suitable for the data can be achieved by means of Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF). The Auto-Correlation coefficient of j-order time series \((s_1, s_2, \ldots, \ldots )\) is established as

\[
r_j = \frac{\sum_{t=1}^{T} (s_t - \bar{s})(s_{t-j} - \bar{s})}{\sum_{t=1}^{T} (s_t - \bar{s})^2}
\]

(10)

The j-order partial autocorrelation coefficient of time series \((s_1, s_2, \ldots, \ldots )\) is defined as below:

\[
\theta_k = \begin{cases} 
  r_i - \sum_{j=1}^{j-1} \theta_k r_{j-k} & j = 1 \\
  r_j - \sum_{j=1}^{j-1} \theta_k r_{j-k} & j > 1 
\end{cases}
\]

(11)

Step 3: Estimation of Prediction Model Parameter

Once suitable prediction model is found, time series is analyzed and estimation of model parameters is done as below:

In case PACF of differenced series show a sharp cut off and also lag-1 autocorrelation is positive then it is assumed that there is need to append single or additional AR terms to the model. The lag away from the PACF cut-off characterizes the quantity of appended AR terms.

As well as if ACF of the differenced series demonstrates a pointed cut-off and lag-1 autocorrelation is negative, then assume to add MA term to the model. The lag beyond ACF cut-off represents number of added MA terms.

Step 5: Selection of Suitable Prediction Model

This step is the most suitable model consisting of suitable predicted data or sensed data is chosen based on Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) for analysis of the model. The calculation for AIC indicator and BIC indicator is given as below:

\[
AIC = -2I / O + 2R / O
\]

(12)

\[
BIC = -2I / O + O
\]

(13)

Here \(I\) represents log likelihood, \(O\) represents number of observations, \(R\) represents right hand side regressors.

Also \(\eta\) in equation (14) represents sum of squared residuals

\[
\eta = \frac{1}{2}(1 + \log(2\pi) + \log(\eta / O))
\]

(14)

The explanation of proposed prediction model is given as below:

In order to construct prediction model based on ARIMA, first sensor node collects all the recent sensed data series \((s_1, s_2, \ldots, \ldots , s_n)\). In case, \((s_1, s_2, \ldots, \ldots , s_n)\) is not stationary, the data series can be altered by means of applying differencing approaches. This approach can be applied to the series of data until the variance among the consecutive data is lower than the application defined fixed threshold \(\eta\). After that choose the suitable ARIMA prediction model based on differenced data series \((s'_1, s'_2, \ldots, \ldots , s'_n)\) using least square technique. The iteration to get the suitable prediction model is done according to Box Search path which is shown in Fig (1). It helps to find best model having lower quantity of exploration time. If BIC pointer of prediction model is lesser than application defined BIC threshold \(\lambda\), then the iteration to find best prediction model stops.

3.4. Data Aggregation Model

This section describes about the data aggregation technique. This involves the selection of most suitable aggregator to transmit the predicted data values.

3.4.1. Selection of Aggregator

The selection of aggregator mainly depends on the three metrics Estimated one hop delay (EOHD) (3.2.1), Time to Deadline (TTD) (3.2.2), and residual series (3.2.5). It can be explained as below:

- An aggregator which has the least EOHD is selected so that all the neighboring nodes containing the predicted data can send it to aggregator easily.
- The TTD is an important factor to choose the aggregator. The aggregator which has less TTD value first to transmit the data to the sink without any delay.
- The node with highest residual energy is selected aggregator.

This can be explained in the following steps:

Step 1: Calculate EOHD for aggregator \(A_i\)

Step 2: Calculate TTD for aggregator \(A_i\)

Step 3: Estimate \(E_{\text{th}}\) for aggregator \(A_i\)

Step 4: Compare EOHD and TTD value of \(A_i\)

if \((A_i\) has less EOHD, TTD value) and \(A_i\) has more residual energy)

then select \(A_i\) as aggregator

else reject \(A_i\)

repeat selection of aggregator

3.4.2. Data Aggregation Technique

Once the aggregator is selected, then all the neighboring node sends their data to the aggregator for transmission to sink as shown in Fig (2). This can be explained in the following steps:

Step 1: First an appropriate prediction model is constructed which is described in section 3.3.

Fig 1: Search Path Model

Step 2: After that all the estimated parameters are sent to aggregators.
Step 3: Next calculate prediction value (P_t) based on prediction model and compare sensed value (S_t) with the predicted value.

\[ \text{if } (S_t - P_t) < \tau \]

then store S_t into data queue table
else store the S_t in data queue table as well as send to the aggregator
If P_t exceeds the fault range of S_t, then rebuild the prediction model and refresh the parameters.
Here \( \tau \) represents the error threshold.
Step 4: After that calculate prediction error (E_s) (3.2.4) and the EHOD (3.2.1) to find the waiting time (equation 1) after which aggregator will transmit the data.

\[ WT = \frac{TTD - (I_s \times EHOD)}{1+ (I_s - 1) / I_h} \cdot \phi \]

Step 5: The aggregator will then send the collected data to the sink, once waiting time is over.

3.5. The Overall Algorithm
This section describes about the overall proposed algorithm

// Selection of Prediction Model//
1. Collect all data series \( \{s_1, s_2, \ldots, s_n\} \)
2. \( H = 0 \)
3. While \( \text{var iance (diff \{s_1, s_2, \ldots, s_n\}, H) - var iance (diff \{s_1, s_2, \ldots, s_n\}, H + 1) > \eta} \)
4. \( H = H + 1 \)
5. Make \( \{s_1, s_2, \ldots, s_n\} \) stationary by \( H \) order differencing
6. For AR \( \rightarrow \) 1 to Max AR
7. For MA \( \rightarrow \) 1 to AR
8. Fit Prediction Model \( (AR, 0, MA) \) model based on \( (S_1, S_2, \ldots, S_n) \) using least square method
9. Calculate BIC indicator
10. If \( \text{BIC} < \lambda \)
11. Break prediction model

12. End if
13. End for
14. End for

// selection of Aggregator
15. Calculate TTD, EHOD
16. If (TTD, EHOD value is less for \( A \) and (high \( E_s \))
17. Then select \( A \) as aggregator
18. Else reject \( A \) and search for new aggregator

// Data aggregation Technique
19. If node is ordinary sensor node
20. While (true)
21. Run selected prediction model with selected aggregator
22. Send calculated parameter to aggregator
23. Do
24. Collect predicted value
25. If \( |S_t - P_t| < \tau \)
26. Data table queue[current index] predicted value
27. Else
28. Data queue table[current index] \[\rightarrow\] Sensed value
29. Send sensed value to aggregator
30. Aggregator sends data after waiting time
31. End while
32. End if

4. SIMULATION RESULTS
4.1 Simulation Model and Parameters
The network simulator (NS-2) [19] is exercised for the estimation of the proposed prediction based energy and delay aware data aggregation technique. In the simulation, the mobile nodes move in a 500 meter x 500 meter region for 50 seconds of simulation time. All nodes have the same transmission range of 250 meters. The simulated traffic is Constant Bit Rate (CBR).
The simulation settings and parameters are summarized in table.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Nodes</td>
<td>20, 40, 60, 80 and 100</td>
</tr>
<tr>
<td>Area Size</td>
<td>500 X 500</td>
</tr>
<tr>
<td>Mac</td>
<td>IEEE 802.11</td>
</tr>
<tr>
<td>Transmission Range</td>
<td>250m</td>
</tr>
<tr>
<td>Simulation Time</td>
<td>50 sec</td>
</tr>
<tr>
<td>Traffic Source</td>
<td>CBR</td>
</tr>
<tr>
<td>Packet Size</td>
<td>512</td>
</tr>
<tr>
<td>Sources</td>
<td>4</td>
</tr>
<tr>
<td>Initial Energy</td>
<td>15.1J</td>
</tr>
<tr>
<td>Transmission Power</td>
<td>0.660</td>
</tr>
<tr>
<td>Receiving power</td>
<td>0.395</td>
</tr>
<tr>
<td>Transmission Rate</td>
<td>100Kb</td>
</tr>
</tbody>
</table>

4.2 Performance Metrics
The performance of the proposed Prediction based Energy and Delay aware Data Aggregation (PEDDA) scheme is estimated based on the following metrics. The obtained results of the performance of the proposed PEDDA scheme are then judged against DAA Technique. The performance metrics are as follows:

- **Average Packet Delivery Ratio**: It is the ratio of the number of packets received successfully and the total number of packets transmitted. It can be represented by the following formula,

\[ PDR = \frac{N_r}{N_t} \]

Where \( N_r \) = number of packets received successfully
\( N_t \) = the total number of packet transmitted.
4.3 Results

1) Based on Nodes
In our experiment we vary the number of nodes as 20, 40, 60, 80 and 100.

Figure 3 shows the delay of PEDDA and DAA techniques for different number of nodes scenario. We can conclude that the delay of our proposed PEDDA approach has 54% of less than DAA approach.

Figure 4 shows the delivery ratio of PEDDA and DAA techniques for different number of nodes scenario. We can conclude that the delivery ratio of our proposed PEDDA approach has 13% of higher than DAA approach.

Figure 5 shows the drop of PEDDA and DAA techniques for different number of nodes scenario. We can conclude that the drop of our proposed PEDDA approach has 84% of less than DAA approach.

Figure 6 shows the energy consumption of PEDDA and DAA techniques for different number of nodes scenario. We can conclude that the energy consumption of our proposed PEDDA approach has 24% of less than DAA approach.

5. CONCLUSION
In this paper we have proposed prediction based energy and delay aware data aggregation technique in WSN. In the proposed technique, first an efficient prediction model is constructed based on time series approximation method. Here all the data set is collected which is stationary and then finds predicted and sensed value of sensors. After that a suitable aggregator is selected based on the estimated one hop delay, time to deadline and prediction error. This selection technique helps to choose reliable aggregator for data transmission without any delay. After that the comparison between sensed and predicted value with the error threshold and then the sensed value is sent to the selected aggregator. Finally, the data is transmitted by aggregator based on the waiting time which is calculated based on estimated one hop delay and residual energy to maintain energy efficiency in the network.

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