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Linear Programmable Load Balanced Data-Gathering in Multisink Wireless Sensor Network

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Abstract: Wireless sensor networks have been the de-facto standard for modern and intelligent sensing in Military applications such as monitoring power systems (viz., solar power) and tactical communications. Efficient and successful data gathering is mandatory requirement in such mission critical applications. Robust network architecture and a new communication protocol are required to achieve it. We propose a multisink WSN with intrinsic and linear programmable load balanced data-gathering protocol implemented in the statically distributed special nodes or advanced nodes. The special nodes links to multiple sink by analyzing the existing route path, its congestion ratio, load factor, least cost route, delivery ratio, energy constraints etc. Simulation and experimental analysis shows that our approach increases the load balancing factor and network lifetime. It also predicts the better way of gathering the mission critical data by applying a fast computation mechanism and lower overheads. The key factors such as communication latency, transmission overhead, packet replication and delivery rate were analyzed and their results were compared with known protocols and methods.

Key words: Linear programmable, load balanced, multisink, data gathering, wireless sensor network

INTRODUCTION

With sophisticated and competitive military wireless environment, the control of the energy consumption in a tactical communication network is very crucial for connectivity and QoS. One way to meet tactical networks demands is to automate energy harvesting from natural resource like solar power with low weight accessories for cost-effective power managed rapid tactical deployment. Major concern with solar power lies in its consistency of power output in varied conditions. In this study, we assume a smart WSN that utilizes automated energy harvesting system using solar power for tactical battlefield operations. The proposed system comprises of Smart WSN integrated to solar concentrators for controlling and positioning for maximum energy harvesting. Furthermore, the wireless sensor at each solar concentrator is connected with MEMS based tracking device and prominent gateway (advanced or special nodes) implements the Intrinsic and Linear Programmable Load Balanced Data-gathering Protocol (ILP-LBDP). Primary objective of ILP-LBDP is to gather data efficiently from multiple sources and route it to an optimal sink in a multisink....scenario keeping BER at 10-3 level. Researchers who work on multisink mechanisms believe that by increasing the number of static sink nodes one can distribute the traffic load all over the network and consequently balance energy consumption around the sink. Finding an optimal location for the sink nodes and looking for low cost paths from each source node to one or several sinks there by providing guaranteed data delivery are the main concerns in this research area. Existing MultiSink and Load-Balance Routing Algorithm (MSLBR) (Wang and Wu, 2009) prolonged network life time through distribution of loads among sink neighbors. MSLBR has on average 7.1 and 14.4% longer lifetime compared to the Primary Based Routing (PBR) and Energy Level Based Routing (ELBR) algorithms. However, the time cost for updating routing table and finding the match deputy for a packet in MSLBR is a bit high. Therefore, the data transmission delay is increased rather more than in the other approaches. Problems such as causing high flooding, control message overhead and increased transmission delay in existing approaches were evaluated and the proposed work was developed to control these issues and enhance effectiveness in accurate data gathering (Tang *et al.*, 2013; Xiong and Tang, 2014; Kong *et al.*, 2015). The proposed research is an efficient mechanism to overcome the said problems by implementing ILP-LBDP in special node.

It performs the following activity. It collects data from sensor nodes, aggregates and forwards data to the most

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optimal sink. It receives control instructions from sink and forwards it to Micro Electro Mechanical Sensor (MEMS) that controls the tracer application device (Didioui *et al*., 2013). This study mainly focuses on the first activity. The second is not discussed in this study. Special attention has been devoted to network load balancing (Yoo *et al*., 2010) using multiple constraints in multisink scenario to enhance network lifetime. The solar power tracking algorithms were implemented using new CO-simulation framework based on MATLAB and OMNeT+(COSMO) (Zhang *et al*., 2010) to rapidly build credible simulations for indoor wireless networks. Experimental results show that ILP-LBDP has higher efficiency in accurate data-gathering w.r.t reduction in packet loss rate, packet replication and lower latency. It obtains efficient load balancing among multiple sinks thereby increasing the overall network life time and ensures fairness. Our scope was limited to analyzing the data received and its accuracy level. In the following sections we discuss how such a ILP-LBDP model which combines (multisink) telecommunication technologies and WSNs, can be realized.

MATERIALS AND METHODS

Intrinsic and Linear Programmable Load Balanced Data-gathering Protocol (ILP-LBDP) architecture: An efficient operation of solar power plant lies in the real time data gathered at centralized location and continuous instruction sent back to Micro Electro Mechanical Sensor (MEMS) for fault management or preventive measure handling mechanism. We keep the data gathering as a primary problem and solve any pitfalls occurring with the help of improved and novel methods. Primary objective of the proposed work is to. Automate energy harvesting for power management in TBA. Perform efficient data gathering from TBAs for monitoring, tracking and initiating remote controlling activity without human interventions. We assume that each solar panel (approx., 10 kw) is integrated with wireless sensor nodes. Highly powered special nodes are deployed at specific geographic locations (mounted on shelter or on vehicles) is depicted in Fig. 1. Multiple sinks are deployed across the network in a way that is capable of receiving data from the special nodes. In our scenario, we have considered four sinks deployed within or outside the geographical area depending on the application requirement. The proposed ILP-LBDP includes the following main components.

Senor nodes: The sensor nodes senses the environment, collects sensory information and transmits the data to its nearest highly powered special node.

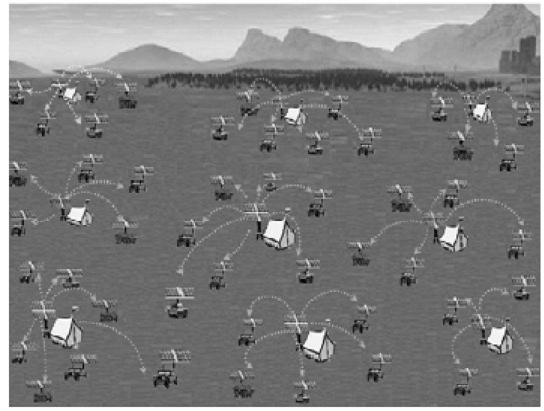

Fig. 1: Solar powered tactical operation center

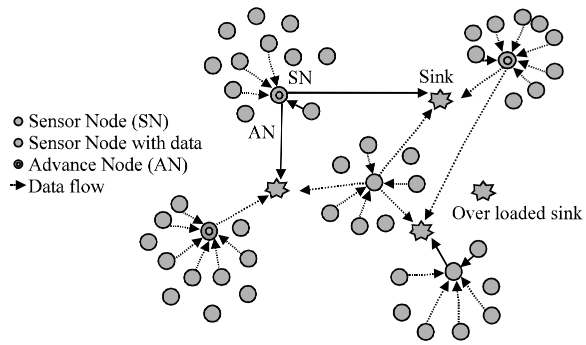

Fig. 2: Network model of ilp network model of ILP-LBDP

Gateway/special/advanced nodes: It is high Power node with larger transmission computing capability. It is advance in terms of memory storage, computing capability and transmission. It supports variable buffer management capable of storing and relaying multiple packets gathered from various sensors. The main role of advance node is to support inter-device communication. The proposed ILP-LBDP is executed by these special node.

Sink: It is the back-end centralized control system. Additionally, it has the Web clien a graphical user interface for final visualization and apprehension. The control system consists of integrated wireless sensors with Micro Electro Mechanical Sensor (MEMS) for tracking and preventive maintenance which is not focused in this study. The network model of ILP-LBDP for Solar Power Plant Control Systems is depicted in Fig. 2.

Route discovery phase: The sensor node transmits the data to its nearest highly powered advanced node. The advance node using LBDP evaluates the following load, delay and distance optimal sink. Figure 3 shows the route discovery phase in ILP-LBDP.

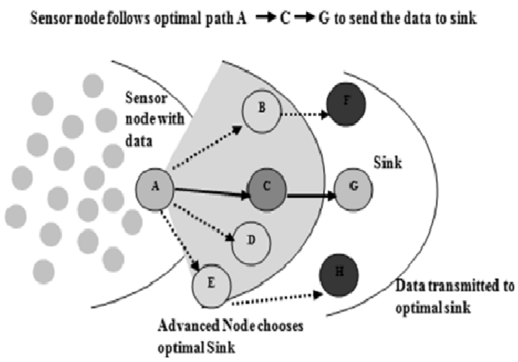

Fig. 3: Route discovery phase using ILP_LBDP scheme

Load: Load status indicates the number of data or control packets in the queue which is processed at each sink at any particular instance of time. The packet arrival, transferring and leaving relationships of the transmission nodes and sink nodes are.analyzed. In our model, data packets are transmitted from multiple advance nodes and processed by the sink nodes. Load analysis using data flow balance equations are obtained to optimize the performance of the network by preventing packet drop caused due to congestion in the path and at the sink node. The congestion situation is evaluated to get real effective arrival rates and transmission rates. The optimal values for packets buffer sizes settings are obtained to derive the threshold limit (α_{load}) for data packets in queue to be processed by each sink. Assume a scenario where a sink receives data packets from multiple advance nodes (node 2-4) as shown as Fig. 4. The advance node has an optimal packet capacity to collect data from sensors, stores, aggregates and forwards to sink. For any sink 'i' in WSN, packet queue length of sink is QL_i^{sink}, then the following relationship is obtained.

$$P_i^{arrival} \sum_{i=1}^{m-1} P_k^{arrival} P_{ki}^{arrival} = \frac{QL_i^{sink}}{T_i^{sink}} + (1-p_{ii})u_i \tag{1}$$

Where:

$P_i^{arrival}$ = The independent external poisson arrival rate of node i, indicates the arrival rate of node k

$P_{ki}^{arrival}$ = The probability of packet arrival from node k to node i, indicates transmission relation of packet queue for sink node i

$T_i^{arrival}$ = The service rate is and gives the service rate is u_i

p_{ii} = Gives the to sink probability

For sink node i in WSNs, the data packets arrival rate is obtained by equation:

$$\lambda_i = P_i^{arrival} + \sum_{i=1}^{m-1} P_k^{arrival} P_{ki}^{arrival} + \lambda_{i\,pii} \tag{2}$$

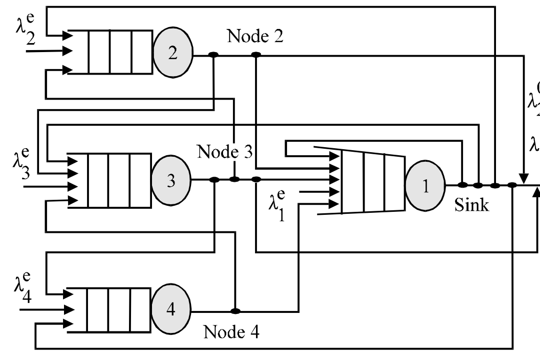

Fig. 4: Packet transmission by multiple advance nodes to sink

At this time, the number of packets is Y_i after the completion of service:

$$X_i = T_i^{sin\,k} \lambda_i \tag{4}$$

Therefore, packets queue length of node i is QL_i^{sink} which is difference between the number of effective arrival and leaving and minus the number of packets being processed.evaluation is critical to analyze multiple sinks load condition and select the best suitable sink with load less than the threshold limit set for efficient data transmission and processing.

Delay: Delay is the time taken by the packet to traverse from sender to receiver. The advance node evaluates measurements subject to end-to-end delay constraint for all sinks in the network. Let us consider a scenario where M sensor nodes collect observations from the surrounding environment. Sensor events (i.e., data packet arrival) is modeled as an exponential inter-arrival times with rates where m = 1, 2, …., M. We assume that the network consists of control and data packets transmitted.

In general, both control packet arrivals and data packet arrivals are assumed to be poisson distributed with rates $Arrival_{Control\,Packet}$ $Arrival_{Data\,Packet} = \sum_{m=1}^{M} \gamma_m$ respectively. Sink node has facility of two priority queue, one for processing the control packets and the other for holding and processing the data packets. Let us consider high priority is given to control packet queue compared to data packet queue. In certain emergency cases, data packets are scheduled and processed using high priority queue with probability $(1 - p_t)$. The proposed work considers both data and control traffic arrive from source to sink. Since, there are two different types of traffic and two different priority queues, the total rate of high-priority traffic T_{high} (and low priority traffic (T_{low}) given by:

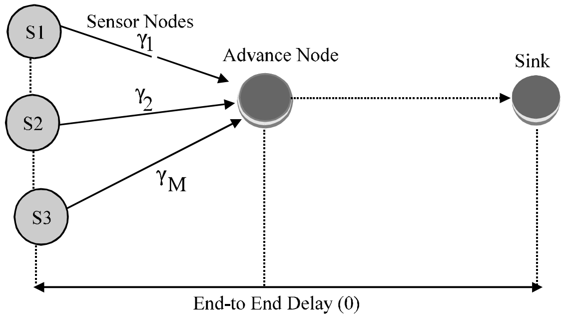

Fig. 5: End-to-end delay between sensor node and sink in ILP_LBDP approach

$$T_{high} = Arrival_{\text{controlpacket}} + (1\text{-pt})*Arrival_{\text{Data Packet}} \quad (6)$$

$$T_{low} = p_t*Arrival_{\text{Data Packet}} \quad (7)$$

To ensure that the Poisson property of traffic is not severely disturbed, we assume that V<< $1/T_{high}+T_{low}$ In other words, the mean inter arrival time of traffic is much larger than mean vacation time (V_i) where i represents the ith node. In order to maintain a predefined QoS, the expected delay experienced by each data packet since its transmission till it reaches the sink node must not exceed a predefined threshold αdelay. Therefore, a data packet with a cumulative delay exceedin αdelay upon arrival to the sink node will be dropped (Fig. 5).

Thus, if D be a random variable that stands end-to-end delay, then the probability of dropping a data packet at the sink node is given by:

$$Packet_{blocking} = Pr\{D > \alpha_{delay}\} \quad (8)$$

Overall average delay is given by:

$$Delay_{Average} = \frac{Packet_{Arrival}\text{-}Packet_{Start}}{n}$$

Where:

$Packet_{Arrival}$ = The time when packet 'i' reaches the sink
$Packet_{Start}$ = The time when ith packet leaves the advance node

'n' is the total number of packets mentioning that the objective is not to minimize packet dropping probability but to select an efficient sink which has the least delay to initiate data transmission and block data transmission to those sink that viola pre-determined end-to-end delay threshold at a particular instant of time.

Distance: In our approach, distance between the advance node and sink node for evaluation.

Implementation of ILP-LBDP using linear programming model: Implementation using linear programming model for suitable sinks selection using ILP-LBDP is illustrated.

Input: The number of sensor nodes S_n^i and advanced nodes A_n^i number of sinks N_{sinks} (the process.
Initialize $first_{count} = 0$; i = 1; $second_{count}$ = ; j = 1 for set of S_k^i nodes
Applying upperbound cut (β_k) to set of S_k^i nodes; *compare Upperbound threshold limit to the number sinks*/
if (sink's Qb_k^i ≤Upperbound cut (β_k) then
/*Store the list of sinks separately in a list and increment the counter*/
Store S $below_k$ data; /* number of sinks selected within this threshold*/
Set $first_{count}$= $first_{count}$+1;
1 = i+1;
/*Check for the number of sinks greater than the threshold limit*/
else if (sink's Qb_k^i ≥Upperbound cut β_k then
Store $Sabove_k$ data;
/* number of sinks selected above this threshold*/0
Set $second_{count}$ = $second_{count}$+1;
end
/*Threshold limit re-adjustment until 50% of sink is achieved*/
if $second_{count}$ >1 then
R-adjust the Upper bound cut value (β_{adjT}) of the sink
Repeat the process
j = j+1;
Until j≤ $second_{count}$
/*Continue until sinks (i.e., 50% of sink) is achieved */
end
end /*end of for loop*/
Repeat the process until 50% of sink selection is achieved.

Output: The set of Sm_k^i nodes selected after applying Upperbound cut (β_k)
Input: The set of Sm_k^i nodes identified after applying upperbound cut (β_j) is given as an input to the Sub Problem (SP).
Gets the count ($sink_{count}$) of sinks
Initialize ($test_{count}$) = I = 1;
if $sink_{count}$ >1 then
Repeat for each sink node S_k^i /* Compare the number of sinks with Lower bound limit */
if (sink's Qb_k^i ≤Lowerbound α_k
&& (sink's sdl_k^i ≤Lowerbound α_k)
Store $Sink_{LB}$ data;
Set ($test_{count}$) = ($test_{count}$) +1;
end
I = i+1;
Until i $sink_{count}$≤ ; /* continue for all sink i.e., all Sinks are processed */
end
Get the count (($test_{count}$)) in order to select best sink node among ($test_{LB}$) /* Efficient Sink selection */
Initialize select $_{count}$ 0; j =1;
if $test_{count}$ >1then Adjust the Lowerbound cut value (α_{adjDL}) of the delay parameter according to their value
elseif S_p^i (nodes distance ($S^p_{dis\leq}\alpha_{adjDL}$) and

$\left(S_p^i \text{ nodes delay } S_{dl}^p \le \alpha_{adjDL}\right)$ Store sink (O_{sink}); /*Store the sink satisfying adjusted lowerbound limit*/
$Select_{count} = Select_{count}+1$;
End /* Re-adjustment of lowerbound limit in order to choose most optimal sink*/
if $Select_{count}>1$then Re-adjust the Lowerbound cut value (α_{sdjR}) of the parameter according to their value
Repeat the process
$j = j+1$;
Until $j \le Select_{count}$ /*Continue until optimal sink is selected*/
end
Repeat from step 1 using step 2 until an optimal sink is chosen by the advanced node.
Output: An optimal sink (O_{sink}) is selected after the iteration process

At first step, the problem identification is initiated. Consider the Problem (P) where indicates selecting most optimal sink among multiple sinks for successful data transmission Using 'P', construct Master Problem (MP) with initial set of constraint (load). Set Upper bound Threshold Limit (U_{TL}) for the buffer size of t queue at each sink. The Upper bound Threshold Limit (U_{TL}) gives the number of data packets in the queue buffer which is processed at each sink at that instance of time. Sink with current load status less than upper bound is filtered for further processing. Subset of sinks derived is at first step, the problem identification is Problem (P), where 'P' electing most optimal sink among nks for successful data transmission. Master Problem (MP) with initial set of constraint (load). Set upper bound) for the buffer size of the queue at each sink. The upper bound threshold) gives the number of data packets in the queue buffer which is processed at each Sink with current load status less than upper bound is filtered for ssing. Subset of sinks derived is further processed using sub-additional constraints (delay and distance) using lowerbound limit (lowerbound limit (α_k) to set of ' S_k^i nodes, the algorithmic steps involved for selecting the most optimal sink is illustrated.

Mathematical evaluation for deriving the most optimal sink among multiple sinks is done considering the current state of the constraints at a particular instant of time. Generate a m×n matrix, where 'm' indicates the constraints (load, delay and distance) and 'n' indicates the number of sinks (S_1-S_4). Assume the following scenario, where one or more sink satisfies the criteria (condition for selecting the most optimal sink), then priority for selecting the best sink for data transmission is given to the sink that has the least delay, load and LBDP computes the column Fig. 6, using the algoritmic process to predominantly verify if there exists a column that satisfies the preset condition, i.e. (sink's $Sb_k^i \le \alpha_{load}$) and (sink's $dl_k^i \le \alpha_{delay}$) and sink's δ min). where Sb_k^i is the ith

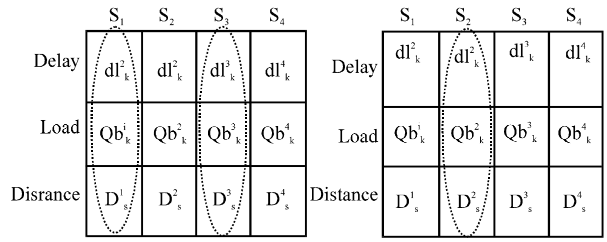

Fig. 6: Column matrix for sink selection using ILP_LPDP scheme

sink node's queuing buffer value for considering overloading factor and i sink node's delay and sink with minimum distance (δ min). Column that satisfies the criteria will be sink selected for data transmission.

Thus, the advance node selects the most optimal sink in the network using the ILP-LBDP. Thereby, the route is established from the source to the sink.

Data transmission phase: Data from senor nodes are collected by their nearest advance node. The advance node acts as a local repository to temporarily store data collected from multiple sensors. After data collection (Kui *et al*., 2013) from sensor nodes, advance node performs additional services such as data fusion, data aggregation (Ji *et al*., 2013; Li and Wang, 2013; Zhao *et al*., 2014; Xu *et al*., 2015) and interpretation techniques and disseminates it to the optimal sink. Sink upon receiving the data updates it to the centralized DB. Sink being the back-end centralized control system, consistently synchronizes data received from advance nodes over time to its central repository. This centralized control system is crucial and is therefore also an essential part of preventive maintenance. Maintenance measures are proactively invoked at an early stage based on the data collected. The collected information represents a vital source of big data for the statistical and research (e.g., detecting faults) activity.

RESULTS AND DISCUSSION

This research proposes a co-simulation framework, COSMO which combines the strengths of two different tools, namely MATLAB and OMNET++ to produce more realistic simulation results. The MATLAB environment is used for modeling the power management system and for data visualization while OMNET++, a precise wireless sensor network simulator is used to implement the communication protocol layers and simulate the network behavior. Both MATLAB and OMNET++ are run

Table 1: Simulation parameters

Parameters	Values
Deployment type	Random
Area size	Topology
Number of nodes	10×10 km
Radio range	15 m
Transmission range	250 kbps
Buffer size	25 packets
MAC layer	IEEE802.15.4
Simulation rounds	1000-3000

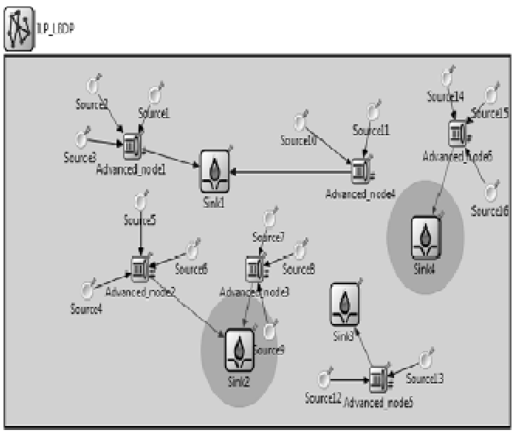

Fig. 7: Network scenario of ILP implemented in OMNET++

interactively and exchange data using sockets. Using the new co-simulation platform, it is possible to simulate the network behavior for several weeks, months or years using the environmental data of a specific location in the world, hence easing the design of a wide-range of novel 58deployment scenarios. Performance analysis was conducted taking into consideration the existing MSLBR scheme. Simulation parameters considered during experimental process is shown in Table 1. Simulation setup considers a Wireless Sensor Network 10×10 km area were sensor nodes (varying from 100-500) are randomly deployed. Multiple sink nodes deployed at most appropriate location (within or outside the sensor node deployment area). Gateways or Special nodes were randomlydeployed within the network area covering most of the sensor nodes. The simulation iteration was varied from 1000- 3000 based on the density of node deployed in a given area. Figure 7 depicts the network scenario of ILP-LBDP implemented in OMNET++simulator where Sink2 and Sink4 are overloaded.

Delivery rate: For analyzing the packet delivery rate in diversified set up, the link loss rates were randomly set to be between 0 and 20%. Simulation was triggered considering randomly chosen sensor node to act as source that tends to generate message and let it send message to the highly powered advance node on varied time slot. Each advance node used buffer to cache

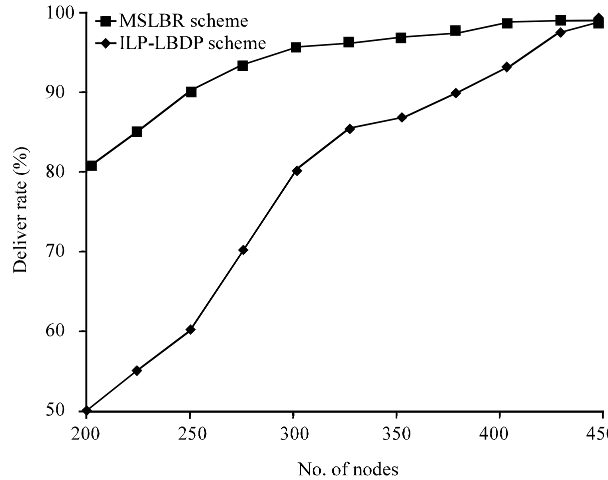

Fig. 8: Average delivery rate

packets sent from its nearby sensor nodes. Advance node then initiates the ILP-LBDP to find the most optimal sink. Analysis was done through dynamically filling sinks node's queue with data (varying from 10-80%) occupation that accounts for load factor.

The simulation results shown in Fig. 8 shows that ILP-LBDP can guarantee the desired delivery rate after the network den reaches a certain level. This is because with the increase of network density frequency of the advance node executing the proposed algorithm also increases which in-turn reflects in the selection of appropriate sink, indicating higher chances for a message to get delivered to the sink successfully. Additionally, ILP reach the desired delivery rate earlier than existing MSLBR scheme. After the network becomes dense enough, for example, with >250 nodes in the 99% desired delivery rate setting, existing MSLBR delivery rate will continue increasing but for ILP rates will keep at the 99% desired delivery rate level.

This is because ILP-LBDP satisfy the desired delivery rate through optimal sink selection proces such as load and delay during the route discovery phase.

Control message and packet replication overhead: The major improvement of ILP LBDP over existing MSLBR lies in the control message overhead and the packet replication overhead as shown in Fig. 9. The major improvement of ILP- LBDP over existing MSLBR lies in the control message overhead and the packet replication shown in Fig. 9a, b). Figure 9a the packet replication overhead of ILP is substantially less than that of existing MSLBR and the reduction in control message 8a average control message overhead. eplication overhead. The packet replication overhead of ILP-LBDP is substantially less than that of existing MSLBR and the reduction in

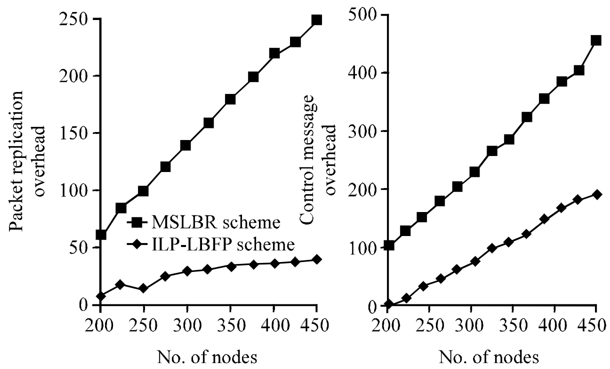

Fig. 9: a) average control message overhead and b) average packet replication overhead

Table 2: Performance comparison with proposed ILP-LBDP and MSLBR scheme

Scheme	Latency comm node	Latency comm gw sink	Transmission overhead (bytes)
Existing MSLBR	8.009 sec	~7 sec	1724
Proposed ILP-LBDP	5.001 sec	~7 sec	1178
Proposed ILP-LBDP improvements	21	0	29

control message overhead in ILP-LBDP is also large even with their initial overhead. This indicates ILP-LBDP processed by special node can save a lot of overhead during selection of sink node by identifying the sink node proactively at an earlier stage compared to the existing MSLBR technique.

Transmission overhead: As discussed before, once optimal sink selection through linear programming model using ILP-LBDP is completed by the gateway node, the sensor Node initiate data communication to the sink via the gateway. Data transmission over size constrained IEEE 802.15.4 radio links, the messages must be additionally split into several packet fragments due to their extensive message size of 16. Transmission overhead comparison was done between the proposed ILP-LBDP scheme and MSLBR scheme. As referred in Table 2 the measure transmission overhead of the MSLBR scheme was 1724 bytes which cause in total of 28 packet fragments for the complete transmission of all messages from sensor node to the sink. In contrast, for the proposed ILP-LBDP scheme the measure transmission overhead was 1178 bytes and it cause 17 fragments totally. As the result, from the analysis it is found that the transmission overhead in the proposed ILP-LBDP scheme reduces by 29% compared to the existing MSLBR scheme.

Communication latency: Latency is defined as the time required from sending a request (from sensor node) to confirming the response (advance or gateway node) between two peers. This metric is vital for time-critical applications such as tactical battlefield domains. To estimate communication latency, the time which is spent from sensor node to the sink ($Letency^{comm}_{node}$) (is calculated).

This processing time deduced from the summation of communication latency from sensor node to gateway ($Letency^{comm}_{node\_gw}$) and from gateway to the sink ($Letency^{comm}_{gw\_Sink}$) which can be written as:

$$\text{Letency}^{\text{comm}}_{\text{node}} = \text{Letency}^{\text{comm}}_{\text{node\_gw}} + \text{Letency}^{\text{comm}}_{\text{gw\_Sink}}$$

In this work, to compute the communication latency from the sensor Node to gateway and from gateway to sink, MATLAB script was employed to track the time taken between each requests and responses. According to our analysis, the proposed ILP-LBDP scheme achieves an almost better latency, it takes up to ~12 sec for complete communication. However, the existing MSLBR approach required communication time upto ~15 sec for complete communication. As shown in Table 2, the latency required for communicating between the sensor node and gateway was about 4.008 sec for the proposed ILP-LBDP approach whereas this time increases to about 8.009 sec in existing MSLBR scheme while the latency time taken for communicating between the gateway and sink was about approximately, 7 sec in existing scheme and approximately, around 6 sec in proposed scheme. Thus, regarding the latency from the sensor node to the gateway, the proposed scheme obtains about 21% improvement compared to the existing approach.

CONCLUSION

Multisink WSN with ILP-LBDP is implemented in the statically distributed special nodes for effective load balanced data gathering in military applications. Using constraints such as the load, delay and distance, the advanced node links to multiple sink by analyzing the existing route path, its congestion ratio, load factor, least cost route, delivery ratio, energy constraints etc. Simulation and experimental analysis shows that the proposed protocol can be deployed in a large scale sensor networks to maintain a higher network lifetime and distributed load balancing. Innovative linear programmable network communication method and dynamic link or topology formation with special nodes are the novel factors of improving the data-gathering, a mission critical factor in Military DAQ (Data Acquisition System) systems. A similar scheme shall also work well for “mobile” sink scenarios with parallel reconfigurable methods to yield fruitful results. Moreover dependability and reliability of “micro-mobile” sink in WSN is a vital challenge that we are looking ahead.

NOMENCLATURE

S^i_k = ith sensor node among ‘k’ nodes
Qb^i_k = ith sink node’s queue or buffer value
dl^i_k = ith sink node’s lower bound delay used i sub problem
β_{adjT} = Re-adjustment of upper bound value
β_k = Upper bound cut value
α_k = Lowerbound cut value
S^p_{dl} = ‘p’ sink node’s delay
α_{adjDL} = Lower bound value adjustment for delay factor
O_{sink} = Optimal sink node
$Sink_{LB}$ = Number of sinks satisfying lower bound limit
$Sink_{count}$ = Sink node counter

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