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NEW METHOD FOR CONGESTION CONTROL IN WIRELESS SENSOR NETWORK USING NEURAL NETWORK

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Resumen: Los trabajos de investigación relacionados con redes de sensores inalámbricos han crecido recientemente. Hay hardware que puede recibir datos multimedia del entorno. Estas redes deben ser capaces de entregar datos multimedia de alta calidad al receptor. En este trabajo se introduce un nuevo método de congestión con características tales como sensibilidad a la demora y sus cambios. En este trabajo se sugiere un sistema que utiliza redes neuronales para detectar la congestión, especialmente en redes de sensores inalámbricos, e impide fallos y paradas en los servicios de red y detecta la fuente de congestión.

Abstract: Research works related to wireless sensor networks have recently grown. There are hardware which can receive multimedia data from the environment. These networks should be able to deliver high quality multimedia data to the receiver. In this paper a new congestion method is introduced with such features as sensitivity to delay and its changes. A system is suggested in this work which uses neural networks for detecting congestion especially in wireless sensor networks, and prevents from failure and stops in the network services and detects source of congestion.

Keywords: Wireless sensor network, congestion control, load balancing, optimized routing, neural network, congestion prediction

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1. INTRODUCTION

Sensor networks are composed of a large number of nodes which collect and process data. Physical position of nodes in the sensor is not necessarily predetermined and the network can be left in dangerous or inaccessible locations and use their data (Rahmati, 2013).

Wireless sensor networks are a group of small sensors capable of partial transferability. Designing this type of networks in the future will need support with service quality requirements. The network in service quality based routing protocols should balance the traffic in addition to promoting its performance (Goozloo, 2010).

One of the limitations of sensors is low capacity of their battery. Using battery energy, sensors collect and measure data and communicate, and ending battery energy means stopping the sensors and part of the network is lost. Routing in these networks is crucial. Current paper addresses theoretical and practical problems of these networks. If there is congestion in a node, it quickly loses its energy. Thus, it is necessary to utilize quick and efficient congestion control mechanisms in these networks. (Jain, Sethi, 2012)

In order to detect the network density, a new approach based on machine learning algorithm and especially neural network is introduced. Innovation of this research is using neural network algorithm for learning load division on multiple channels. It is done in order to prevent from buffer congestion of routers. Therefore the congestion is well identified and eliminated.

Although protocols have suitable quality in improving energy consumption, there is no guarantee for the quality of provided service and confrontation with heavy applications. In this paper, balance is made among the factors affecting routing algorithm quality such as network lifelong, delay in data transmission, and coverage in the network, and they are regulated by providing a coefficient for each factor so that the service delivery is optimal.

2. METHODOLOGY

The proposed method is able to identify source and origin of the congestion. Following identifying the node, the matching system applies current speed limit policy, and the congestion is eliminated. Neural network is used in modeling non-linear and time variable systems for predicting traffic current and congestion control. A controlling agent in the base station monitors wireless sensor network and calculates traffic statistics of each node. Controlling agent collects data for all nodes and normalized existing values and easily decides about location of congestion (Mota & Xavire, 2012). Process neutral network teaching, error, and traffic in the previous moments have optimal impact on the network performance. Congestion can be prevented by changing routes of data transmission or postponing the transactions. Output of artificial neural network indicates probability of traffic occurrence in the network points, and predicts the future traffic and in this relation, remaining energy factor is also given in the prediction.

In this paper, parameters related to service quality including end to end reliability, end to end delay, and network lifelong are defined. In addition, a new exploratory mechanism is introduced in wireless sensor networks for awareness of congestion and controlling it. Neural network is used for predicting data transmission delay between the nodes and consumed energy.

For the sensor nodes, distance to the sink and requirements of cost function calculation should be taken into account. Therefore, the sensor nodes should only have direct data about their neighboring nodes. Since the sink have infinite sources, it is responsible for selecting the routes, their numbers, and allocation of data package strategy on each path, and hence end to end requirements, delay, and increasing network lifelong can be obtained. When transmitting data in the route, accounting data related to each node, including remaining energy and time distance between source and target is also added to the transmitted message. Finally, the neural network embedded in the sink performs well the training and evaluates it by simulation and compares it with other models.

Formulation of Service Quality Routing Problem

Model and Network Hypotheses

Wireless sensor network is modeled with N nodes and sinks as unidirectional chart at level („ „) and s sets are vertex representing communicative sensor nodes. L are edges which show link between the nodes and Q denotes non-negative capacity vector of service quality of each edge. The distance of a direct link between sx and sy nodes is $d_{sx,sy}$ A route is defined as a sequence of links of source to sink node and =={path1, path2,.. . , path}} is sum of available routes with discrete nodes between source and sink node. It is assumed that sensors are homogeneous and transmission radius of all sensors is the same as a, and the same energy is consumed to transmit a bit of data.

It is also assumed that sensor nodes are fixed and sensor node at every time can calculate its available energy level (E_{ava}) and records performance of the link between itself and neighboring nodes in terms of delay (D_{link}) and reliability (R_{link}), where R_{link} is expressed in terms of signal to noise ratio (SNR). It is assumed that each node identifies its exact situation, situation of nodes in its communicative range, neighboring nodes, and the sink node by localization method.

Energy Consumption

The energy consumed for data transmission (Epath) from sensor to sink node on a single route is as follows:

$$E_{path_p} = \sum_{l=1}^{hop_p} E_{con_l} \tag{1}$$

Where step p is the number of path step ,, ≥≥≥≥1 and C_{con} denotes energy consumption.

2-c_{con} = ₊+ is stated here which us fir energy Consumption for receiving and transmitting b bits of data between sensor nodes. This energy model was taken from (Elson & Girod, 2012) where there is state of $e_{ix} = (e_t + \varepsilon_{amp} \times a^2) \times b$ and = (×)) and et and er denote energy consumption for transmitting and receiving one bit of data, and a_{amp} denotes transmission amplifier energy consumption. When sensors have constant communicative radius a, some nodes are placed randomly at the distance between region [22], and there is state c_{con} (+ + a_{amp} × 2^2)×b.

c_{con} (+ + a_{amp} × 2^2)×b. To transmit bits of data packet b, the available energy (a_{ava}) must be greater than or equal to the minimum energy threshold needed to transmit this r_{req} packet. In multi-mode routing, total end-to-end energy consumption, e_{e2e}, is measured for transmitting any data packet as a sum of energy consumption across all routes used and is presented as follows:

$$E_{e2e} = \sum_{P=1}^{nP} E_{path_p} \tag{2}$$

In above Equation 7, is the number of multi-mode routes with discrete node for routing data packet. It is assumed that energy consumption is not considered in the receiver nodes which hear transmission randomly. Then objective function of energy (f_E) can be considered which minimizes energy consumption on all routes.

Delay Criterion

Delay is time of transmitting data packets from source to target node. The delay criterion between the two links (l_{link}) is the total processing delay, queuing, transmission and dissemination. Most of emerging sensor networks contains delay-sensitivity programs with real time delay constraints, and thus an efficient routing method is needed to reduce the delay. Path delay (P_{path}) is sum of delay in all intermediate nodes along the path:

$$D_{path_p} = \sum_{l=1}^{hop_p} D_{link_l} \tag{4}$$

To this end, end-to-end delay for transmitting data packets to the sink along with the path or selected paths is given as follows:

$$D_{e2e} = \underbrace{max}_{1 \le P \le np} D_{path_p} \tag{5}$$

Delay objective function assures that end-to-end delay on the selective paths is as $e_{e2e} \le r_{req}$ and parameter r_{req} is user-specific, which specifies required end-to-end delay for data transmission.

Artificial Neural Network (ANN)

Artificial neural network algorithms are among the most accurate classifying algorithms and linear and non-linear predictors, and they are used for prediction (Tan & Dinh, 2013).

Stimulation Functions

By applying a weight matrix w, the input values to the neuron are weighed, and these values will be the actual value of neuron output by stimulation function:

$$l = W \times P + b$$
$$a_{out} = f\ (n)$$
P: Input vector
a_{out} : Output vector
f : Stimulation function

(6)

Stimulation function is selected given the problem, and limited number of them are used. The functions used in engineering include linear stimulation functions, binary function, sigmoid stimulus function, or hyperbolic tangent stimulus function (Jiang, 2015). Figure 1 indicates multilayer neural structure. A bi-layer architecture is used between input and output, where the first layer is implicit and second layer is external. Sigmoid stimulus functions are used.

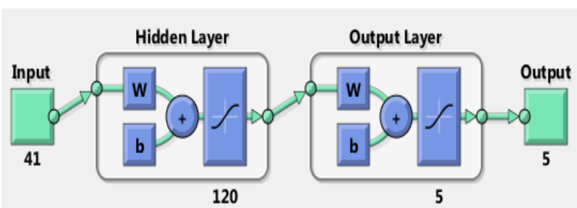


Figure 1. Neural network structure in this research

Sigmoid Stimulus Function

This function confines input between zero and one, and values of its changes are non-linear, and its advantage is that makes the inputs small or large. When the input values tend to large negative numbers, the function has a value of zero and when the input values tend to zero, the function goes to 0.5 and when it approaches the large positive values, the function tends to one, and the relation is defined as follows:

$$f(n) = sig\ (n) = \frac{1}{1+e^{-n}} \tag{7}$$

In this paper, the number of layers is 3 and neuron should be put in the size of dimensions of each input model. Input data determines size of input layers, and three parameters are considered for each node in the network. The number of inputs is n*3. There should be neuron in the same number of nodes in the output layer. In ordinary state, it is excepted when input of a class enters, it leads to neuron 1 congestion, and remaining neurons get zero. But in practice, output value of the network is a value including one an zero. The neuron which is lighted more than others, specifies the class related to that data. There is no specific basis regarding intermediate neurons. If the network is too complicated, and test data changes toward the training data, the network cannot recognize them. Then neuron output function should be determined, and acts in neural networks with error back propagation algorithm. For this purpose, sigmoid function is selected, because it can be easily derived.

Neural Network Model for Energy Estimation and Point-to-Point Estimation

A wireless sensor network with environmentally distributed sensors is considered. A sensor is at sleep state and it is awaken when it is warned by other sensor. In this paper, transmission between various sensors with multiple steps is for communication between source and target node, and information are reported to the sink. In order to determine the node status, data is dynamically controlled. Each message includes control and data parts. In control part, information is related to the nodes transmitting from source to sink, and it is updated. Each node in sink has a table. Whenever the node is transmitted between the source and sink, an entry of the table is put in the sink. In this entry such information as network current time, node's energy at the moment of transmission, delay of data transmission to next node are considered. There is a learning machine in the sink based on artificial neural network where the node at the moment t+1 is based on the network history from moment 0 to t as input, and this information is used for predicting remaining energy at moment t+1. Remaining energy for Q and delay in transmitting information from A to B is stored in the transmitted packets (Hederman, 2015).

This model considers knowledge related to the available paths to the sink for the source and all intermediate nodes for neural network in the sink. This protocol considers the sink to be initiator of the request. Sink is flooded by a request and will put the target at its vision. With flood operations, multiple paths are created in intermediate nodes to the sink. In the router protocol, a request goes to the source from sink using a path ID which is identification number of the first sensor's node. The paths are determined considering the quality desired by the user such as path length, available energy, and estimated lifetime or other basis. Sink is able to develop the network's history table and update it. This table contains following records:

Pid: path ID
inUse: it is flag denoting the respective path is in use at the moment.
Energy: amount of energy
Delay: transmission delay up to the next step

Predicted information is the basis for decision making in the next phase. Thus, no node is never congested in terms of bandwidth and energy. All sensors have limited energy and they are fixed and are capable of changing their transmission power dynamically. It is assumed that addressing system is used. Addressed are highly costly in terms of bandwidth and energy consumption. Therefore, local addressing is used. An addressed is uniquely allocated to a sink.

Strategy of load re-division is used here for congestion control. This state refers to scenario of load re-division absence and identical path in terms of lifetime and data transmission delay is used for congestion control. In each intermediate node, when the queue is greater than the threshold or when the collision rate is higher than this threshold, the congestion notification message is issued for each path identification number by the neural network.

The system introduced in this paper is a routing algorithm in wireless sensor network with mobile nodes. The aim is providing a protection mechanism for on line queuing. The system proposed in this work tracks delay between nodes as point-to-point and thus artificial neural network is used. Non-linear and fixed data sets such as queuing delay, Artificial Neural Network (ANN) are used for prediction which have better compatibility and learning compared to other static and simple prediction methods such as movement average and exponential smoothing. Parallel structure of artificial neural network considerably helps data processing.

Artificial Neural Networks Used for Queuing Time Prediction

The plan is based on queuing delay prediction. The set prediction is an approximate time of the network's function. Artificial neural network is composed of a group of connected neural cells.

Measuring Average Queuing Delay

In this paper's protocol, queuing delay can be divided into three elements:

1. The time needed for discharging packets from the queue in the node to wireless channel, it is totally discharged and determined by traffic load and nominal bandwidth (maximum bandwidth capacity).

2. Accumulated time, avoiding collisions, including waiting time for emptying the channel that is currently busy.

3. Back-off time and other accumulated overheads related to access control to the mediator and time required to get the channel.

The first part is influenced by the network's load traffic and nominal bandwidth. The second and third part is more dynamic than queuing delay, and influenced by the load traffic and the node's topological changes affect the neighboring nodes. Queuing delays are predicted. Delays can potentially reduce path routing fluctuation. Predication of overall queuing delay is highly difficult. The current solution is avoiding accidental channel conflict and focus on the first segments of the queuing delay. The main calculation of queuing delay is based on supreme virtual queue FIFO (First In First Out), and rate of exiting queue is based on nominal bandwidth. Queue size is as follows:

$$V_i = S_{i-1} - (t_i - t_{i-1}) \times B \tag{8}$$

Where $S_{i-1} = V_{i-1} + h_{i-1}$ and $V_1 = Q_1$. In this Equation 8, v_i is size of FIFO virtual queue exactly before exit of i^{th} packet from the queue, S_{i-1} is size of FIFO virtual queue after exit of $(i-1)^{th}$ packet from the queue, h_{i-1} is size of $(i-1)^{th}$ packet exited from the queue, t_i is the time when i^{th} packet is exited from the queue, B is constant nominal bandwidth and Q_1 is real size off queue before exit of first packet during measurement period. Average queuing delay of k^{th} period is simply as follows:

$$\frac{\sum_{i \in P} V_i / B}{Nk} \tag{9}$$

Where P is accumulation of all packets exited from the queue in k^{th} period, V_i is size of calculated queue using Equation 1, B is constant nominal bandwidth, and NK is total number of packets exited from the queue in k^{th} period. Routing decision maker with strong information should be provided for predicting delay. Average queuing delay indicates local traffic load and helps balancing the traffic.

Overall Structural Description

Artificial neural network models appropriate for prediction are taken into account in this work. MLP and RBF networks for delay prediction are used for efficient training of artificial neural networks. There are two specific artificial neural network models and ARX input model is used for proposed delay prediction, which utilized basic average delay values and direct effective factors such as traffic load. In most prediction programs, only the time series are as input. A time series is a set of factors influencing delays in a dynamic environment. These inputs are adequate and artificial neural network can train from time series pattern for disclosing time series. If an effective factor can be identified, considering this factor as excessive input can help acquiring dynamics for time series.

The basic difference between MLP and RBF networks is related to different approaches of approximation for target pattern level. MLP model uses parsing target pattern level from hyperplanes, while RBF uses hyperspheres. Thus, a MLP network of internal product is fed from input to neural cell, and uses active sigmoid ring functions while an RBF network feeds a neuron with Euclidean distance between the input vector and the central vector through the weights. General form of a ring function is as $\varphi(v_j)$=1/(1+exp(-(-v_j)) , where v_j is input level (weighed sum of all inputs) of j neural cell. General form of Gaussian function is as $\varphi(x) = \exp(-\beta|x - c_j|^2)$ where $|x - c_j|$ is Euclidean distance between input vector x, and center of basic function of C_j in neural cell j and β is the weight applicable in learning process.

Gaussian function is larger than sigmoid, and in each iteration of learning, a RBF network can be more invariant than the MLP network. Therefore, if learning data are not misleading, RBF network can be convergent quicker than MLF network. The radial activation function causes the RBF network to have a hidden layer. Structural parameters of these four models include as follow:

- Basic input size (n_a)
- Number of hidden layers (n_l)
- Number of hidden neural cells (n_h)
- The number of periods related to the future which is covered by a prediction or size of prediction window (PW)
- Size of learning data sets (Size_t)

This problem is well identified and one layer of hidden neural cells can manage mathematical complexity of most systems and more than two layers of hidden neural cells are usually considered. The main parameters are length of lagged inputs (n_a) and number of hidden neural cells (n_h) which determines capability of artificial neural network learning. Putting n_h mildly and more than n_a is often adequate.

Comparing Learning Efficiency in MLP and RBF Neural Networks

At runtime, the lag time series are predicted and the learning efficiency of the MLP and RBF network is important. Two efficient features are sensitivity to educational data and training speed. MLP networks are generalized in input space, that is, where there is little or no educational data, while RF networks are trained quicker. Prediction test is done for approving features on combined lag time series. Precision of prediction and training time are inherent in artificial neural network models and should be used in any static time series. When the prediction performance is declined due to increasing irregularities of time series, there would be no difference between two models of neural networks anymore. A combined lag time series is used to show this difference.

Using Genetic Algorithm for Path Selection

The main challenge of genetic algorithm is determining number and location of head clusters. Conventional clustering algorithms use exploratory methods. In this paper, genetic algorithm is used for determining location of head cluster which consumes minimum energy. In the base station, the number of nodes determined as candidate head cluster specify chromosome length in the genetic optimization method. Chromosome structure is as follows:

$$chrom = \{ g_i \mid i = 1,2,3, \dots, l\} \quad (10)$$

Where l is chromosome length and g is i^{th} gene.

Finally, after determining the intersection and mutation, the base station selects a chromosome with a minimum difference in energy toward the previous round and identifies the existing nodes as the cluster head to the network, and the other nodes will join the nearest cluster. Current network energy in k+1th round using neural network in the previous phase and based on the network's history of transmission is shown. The fit function is calculated using Equation 4-3. Which should be minimized. In Equation (4), | | is the symbol of absolute value.

$$fitness = |E^{k}_{Network} - E^{k-1}_{Network}| \quad (11)$$

In genetic algorithm, in random process, population primary generation, crossover and mutation, r = 4 mapping is used. This is a one-dimensional mapping and is represented by Equation 5-3.

$$X_{n+1} = r \times X_n \times (1 - X_n) \quad (12)$$

Base station collects information related to status of each node from each cluster. It is expected that head cluster nodes stay in the covered region. It is also expected that all sensor's nodes in the cluster are connected through direct links.

In this paper, in order to evaluate the quality, the proposed method is implemented and results obtained from simulation will be described in detail in the next section, and it is analyzed in terms of different factors.

Features of Implementation Environment

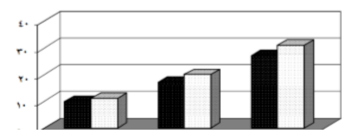
MATLAB R2010a software was used for implementing the proposed method. This simulation was run on a computer with a corei7 processor and 4 GB original memory chip on Windows 7 operating system.

In order to increase probability of finding the paths, a network is selected in which 50 - 100 nodes are distributed randomly in a land of 100 × 100 m area. Simulation time was 1,000 s, and data packet size is 128 bytes with a packet size of 1 packet per second. To this end, total number of data packets transmitted through this simulation is 1000, pkttotal. The source nodes are random and the sink is placed at left top side of simulation region. Provided results are an average of 10 simulation runs. It is also guaranteed that obtained results can be directly compared with the results published in previous works. In higher node densities, probability of finding paths with discrete nodes is increased.

3. EVALUATION RESULTS

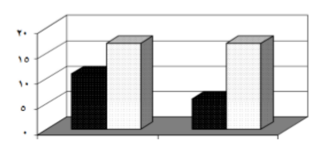
Congestion Identification

Results in Figure 2 diagram indicate that this program detects and modifies congestion in almost 90 percent of cases. Failure means losing modification or congestion prediction in places where there is no specific problem. In 11 states without congestion, the proposed method acted successful in 10 cases, and in cases with observed congestion, the proposed method identified 27 cases out of 31 cases well.



	Without congestion	With congestion	Total
Correct prediction	10	17	27
All cases	11	20	31

Figure 2. Diagram for evaluating accuracy of prediction by proposed method



	Discovery before data packet loss	Discovery up to 3.5 s after data loss
Congestion discovery	10	17
All predicted cases	11	20

Figure 3. Evaluation of proposed method's quality

Figure 3 indicates that congestion has been predicted in 60 percent of cases. In cases where the packet fall prevention was not possible, the network was returned to steady state within 3.5 s.

Previous studies (Zawodniok, 2007) and (Gholipour, 2015) is used for comparison. Accuracy of the proposed method is 87 percent. The diagram below shows results of the comparison.

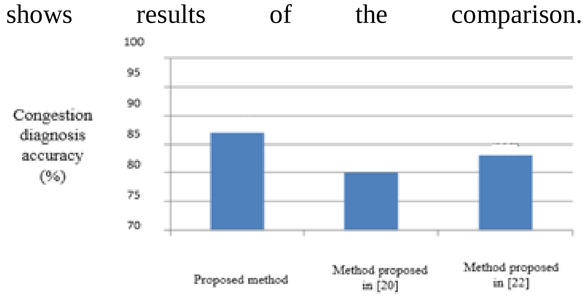


Figure 4. Comparison of accuracy of different methods

As observed in the results, proposed method is more accurate than previous methods.

Point - to - Point Delay

Figure 5 indicates average point - to - point delay in transmitting the packets. The method proposed in this paper has fewer average point- ti -point delay compared to previous method in transmitting the packet, which suggest acceptable quality of the proposed method.

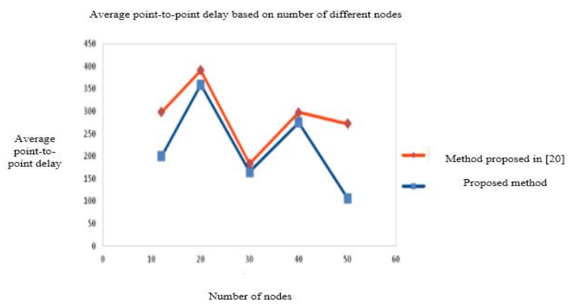


Figure 5. Diagram for evaluating average point- to -point delay in proposed method

Packet Delivery Rate

Figure 5 indicates packet delivery rate in the proposed method compared to the previous method. The proposed system identifies and eliminates congestion by applying current speed limit policy.

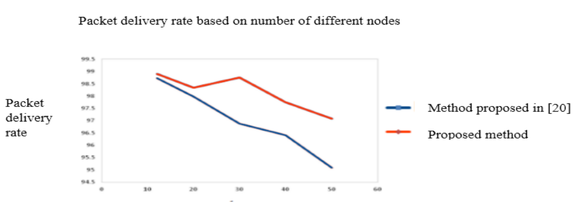


Figure 6. Diagram for evaluating packet delivery rate in proposed method

4. CONCLUSION

The proposed system in this paper uses neural networks for discovering congestion (in wireless sensor networks) prior to failure in the network, and identifies source of congestion. By applying current rate limit, this system avoids congestion which causes overflow of routing intermediate memories. It should be noted that the solution in the form of current rate limits can be used also for the main current source. Designs and experiments provided in this paper can be used also for other network problems. Of course, for this purpose, the main current source should be in the area controlled by the system. It seems this approach can be used for other problems too, and congestion prediction is just the first step toward our desired research goal. Results obtained suggest acceptable quality of this method compared to other methods.

REFERENCES

Rahmati, Q. V. (2013). A New Method for Congestion Control in Wireless Sensor Networks, National Conference on Computer and Mechanical Engineering, Iran, Mayandoab.

Goozloo, A. (2010). Evaluation of Network Congestion Control Mechanisms, 1st Iranian Student Information Technology Conference, Sanandaj, Kurdistan University.

Liu Q. & Czylwik, A. (2014). Study on Adaptive Priority-Based Service-Differentiation Scheme for IEEE 802.15.4 Wireless Sensor Networks. Bismarkstr, Duisburg, Germany.

Kharb, K., Sharma, B. & Aseri, T. (2016). Reliable and Congestion Control Protocols for Wireless Sensor Networks, *International Journal of Engineering and Technology Innovation.*

Kang, J., Zhang, Y. & Nath, B. (2007). Topology-Aware Resource Adaptation to Alleviate Congestion in Sensor Networks. Rutgers University.

Ch. T. Ee and R. Bajcsy, “Congestion Control and Fairness for Many-to-One Routing in Sensor Networks”, SenSys Baltimore, Maryland, USA.

J. Paek and R. Govindan, “RCRT: Rate-Controlled Reliable Transport Protocol for Wireless Sensor Networks”, ACM Transactions on Sensor Networks, 2010.

Sh. Chen and N. Yang, “Congestion Avoidance based on Light-Weight Buffer Management in Sensor Networks” IEEE Transactions on Parallel, 2006

Y. Cao and Z. Sun “Routing in Delay/Disruption Tolerant Networks: A Taxonomy, Survey and Challenges”, IEEE Commun, 2013.

M.A. Talaat, G.M. Attiya and M.A. Koutb, “Enhanced TCP-friendly rate control for supporting video traffic over internet”, Canadian Journal of Electrical and Computer Engineering, 2013.

P. Pham and S. Perreau, University of South Australia: ieeexplore, 2002.

L. Popa, and, IEEE, 2006.

JB. Othman and A. Ouadjaout, “Interference-Aware Congestion Control Protocol for Wireless Sensor Networks”, Procedia Computer Science, 2014.

A Stateless Protocol for Real-Time Communication in Sensor Networks”, International Conference on Distributed Computing Systems ICDCS, 2003.

Predictive Congestion Control Protocol for Wireless Sensor Networks, 2007.

M. J. Neely and L. Tassiulas, “Resource Allo cation and Cross-Layer Cont rol in Wir eless Networks”, the essence of knowledge, Boston - Delft, 2006.

Gholipour, M., Haghighat, A. T., Meybodi, M. R. (2015). Hop-by-hop traffic-aware routing to congestion control in wireless sensor networks, EURASIP Journal on Wireless Communications and Networking.

A. Majidi, H. Mirvaziri, “New Mechanism for Congestion Control in Wireless Multimedia Sensor Networks for Quality of Service and Network Life Time”, American Journal of Computing Research Repository, 2014.

Djenouri, “Congestion Detection Strategies in Wireless sensor Networks”, International Conference on Emerging Ubiquitous Systems and Pervasive Networks, 2014.

V. Chandra, S. shiwani, “Fuzzy Neuro Approach for Active Queue Mangament”, nternational Journal of Computer Applications, 2015.

HB Liaqat, L Liu, J Ma, Journal of Computer and System Sciences, 2016.

W. J. Chang, P. H. Chen and CH. T. Yang, “Robust Fuzzy Congestion Control of TCP/AQM Router via Perturbed Takagi-Sugeno Fuzzy Models”, International Journal of Fuzzy Systems, 2013.

V. Mor, H. Kumar, ACM acknowledges, 2016.