Two-Level Mapping to Mitigate Congestion in Machine to Machine (M2M) Cloud

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***Abstract*—This work focuses on mitigation of the network congestion in a Machine to Machine (M2M) cloud. Since the inception of M2M cloud communication technology, the number of M2M devices has radically increased. This has consequently increased the overall traffic of the network which, in turn, makes the entire network congestion prone. The work assumes an underlying clustered network topology of the M2M devices. We propose a hierarchical congestion control scheme in which we distinctly manage the network traffic by a two-level mapping – i) from the cluster heads (CHs) to the sink nodes and ii) from the sink nodes to the cloud gateways. To ensure "fairness", the mapping is based on the *Theory of Social Choice*. Results are demonstrated at the end which provide fair allocation of CHs to sink nodes and sink nodes to cloud gateways.**

***Index Terms*—Congestion Control, M2M cloud, Theory of Social Choice**

I. Introduction

Due to the advancement in the field of telecommunications, M2M communication is of great significance today. M2M technologies allow systems to communicate from one machine to another through wired or wireless networks. Recently, wireless sensor networks (WSNs) have gained prominence and popularity. WSNs can even make use of cellular technologies for communication. The nodes in this network can be static as well as mobile. Contemporary sensor nodes report the sensed data of various applications to multiple data processing units. The issues of heterogeneity in the data and the management of the bulky data volumes are handled using cloud computing servers thereby, giving rise to M2M clouds [1]. However, due to the voluminous nature of the generated data, the network routes from the physical sensor nodes to the M2M cloud encounter severe traffic which generally lead to heavy network congestion.

The paper addresses the aforementioned problem through a hierarchical congestion control mechanism from the WSNs to the M2M cloud.

A. Motivation

Contemporary data generated from the physical sensor nodes are highly heterogeneous and are generated in large volumes. As previously mentioned the network routes from the data sources (the sensor nodes) to the cloud get highly overwhelmed with the network traffic that leads to unavoidable congestion. This, in turn disintegrates the entire network.

In most of the works, it is assumed that the underlying WSNs follow a clustered topology [2] [3], in which the cluster head (CH) of every cluster report the data from the individual components of a cluster to one or more sinks, which in turn transmit the data to the M2M cloud through the cloud gateways. Congestion can happen at the sink level due to the transmission of data by multiple clusters. In a WSN, sensor nodes sense data on triggering an event and transfer it to the upstream node. This might result in congestion at the upstream node if multiple sensors send data at the same time resulting in the loss of data. So groups of nodes are formed in to clusters for efficient management and a CH is appointed for each cluster. Situations arise where data from all CHs are directed towards the same sink node resulting in the congestion at the sink node.

Data collected at the sink level from the clusters is forwarded to the gateways in the M2M cloud. Congestion might occur even at the gateway because several sinks may forward the data flow to the same gateway in the M2M cloud. It can even occur as servers at a particular gateway might be busy. This results in the loss of data at the gateway and increase in the network load due to retransmissions.

B. Contribution

In this subsection, we discuss the contribution of the work. In our case, congestion can happen at three levels – within the clusters, at the sink nodes and at the cloud gateways.

- *Within the clusters*: We enforce the CH of a cluster to take care of the congestion within the cluster by assigning weights to the nodes based on criterion like priority of the data, energy of the nodes and mobility of the nodes as discussed in [4]. In case of congestion, the CH triggers rate adjustment procedure and reduces rate of the nodes according to the weights assigned thus controlling the load on the network.
- *At the sink nodes*: The work contributes to mitigate the congestion at the sink nodes, by uniformly assigning the CHs to all the sink nodes without over-burdening a single sink node. Data at the sink level are given priority according to the energy of the component sensor

nodes of the clusters, priority of the data sent by the sensor nodes and volume of the data. Moreover, the sink nodes maintain fairness among the CHs being assigned to them such that no cluster is favored in the process of allocation. In the case of congestion, a sink advertises its packet service ratio and scheduling rate so that the clusters divert the traffic generated by them towards the other sink nodes which are in their transmission range. The work implements the *Theory of Social Choice* [5] to overcome the difficulty in the problem by applying "fairness" based strategic voting on the society of cluster nodes.
- *At the cloud gateways*: The work also ensures fairness even at the gateway level for mitigating the congestion. The concept of Theory of Social Choice is also incorporated at the sink-gateway interface is to ensure social welfare in the society of sink nodes

Hence, in this paper we propose techniques based on Theory of Social Choice for hierarchical mitigation of congestion at the three levels. The goal is to enhance the successful delivery of the packets to the cloud for further processing and analysis.

C. Organization of the paper

The rest of the paper is organized as follows. Section II highlights the work done so far on this domain. The problem statements is presented in Section III. The system model is depicted in Section IV. Section V illustrates the implementation details of the work. Section VI evaluates the performance of the system. Finally we conclude the work in Section VII.

II. Background

Of late, contemporary research has explored significant protocols to deal with the data traffic in heterogeneous WSNs. Monowar *et al.* discusses PHTCCP [6] which focuses on the congestion control in static WSNs. Some of the protocols are also explored to control congestion in mobile WSNs. In [4], Ahmad *et al.* proposed TSEEC for handling congestion within mobile WSNs. These protocols mentioned about the various mechanisms about controlling congestion on a hop by hop basis. But all of the work address the problem in terms of assigning weights to the nodes based on some factors like heterogeneous data priority, energy efficiency mobility, and even fairness of the nodes. But the task of mitigating congestion control and implementing fairness at the sink level is subjected to various constraints and is not properly explored.

The same problem arises even at the sink-gateway interface in order to ensure proper communication and prevent data loss. A good number of work has been done on distributing load among cloud gateways under consideration of bandwidth [7] and delay [8]. Congestion control with fair resource allocation for cloud computing environments is discussed in [9].

In this work, we use the Theory of Social Choice which achieves fairness and thus provides social welfare to all the CHs. It is even applied to the gateway-sink interface so that there is fair allocation of cloud gateway nodes to all sinks. This results in mitigating congestion at the cloud gateways which enhances the throughput.

III. System Model

In this Section, we describe the system model. In M2M network a group of sensor nodes are deployed for sensing and transmitting information to the sink node which is ultimately processed in a cloud. Each of the nodes can sense different types of data at the same time and send it to the sink nodes. Here group of sensor nodes are organized as clusters [10]. Nodes can even be mobile and move across clusters.

Motivated by the implementation of the Theory of Social Choice in [11] [12], we implement the system model as follows. The network setup comprises sensor nodes which report the data to the CHs. The CH, in turn, forwards it to the sink nodes which finally pass the information to the cloud gateways [13]. Gateways in turn forward the data to the cloud servers. The computations are performed in the servers and the results are sent back.

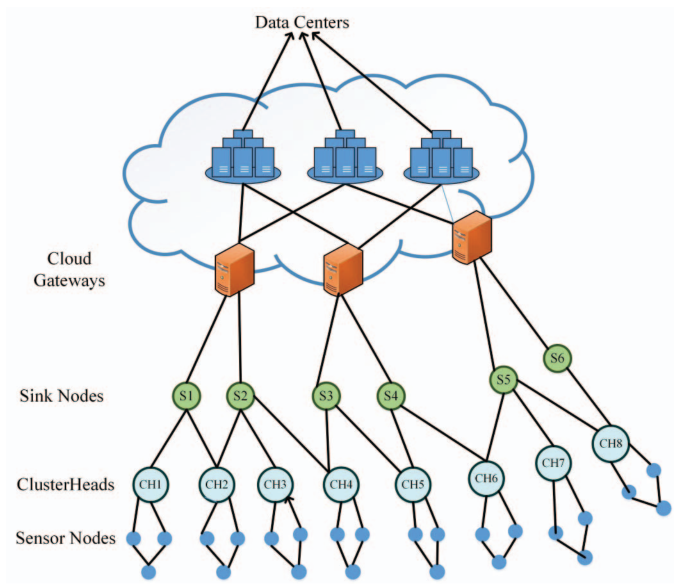

Figure 1: Network Model

Figure 1 depicts the model of our network where groups of sensor nodes are organized in the form of clusters. These CH of a cluster forwards the data to the sink node which has higher computational power as well as buffer capacity. A CH may be connected to one or more sink nodes through which it can forward the data to the cloud gateway. Suppose there is a set of n CHs, $CH = \{CH_1, CH_2, CH_3, ..., CH_n\}$, and a set of m sink nodes $S = \{S_1, S_2, S_3, ..., S_m\}$, $m \ll n$, and a set of k gateway nodes $G = \{G_1, G_2, G_3, ..., G_k\}$. Our goal is to perform a two-way mapping between CHs and sink nodes and also between sink nodes and the cloud gateways for data transmission. Data is transmitted or forwarded through these mapped nodes to the cloud where it is processed. Load on a particular node need to be balanced at every level i.e., the load on the sink node or the gateway node, to prevent over-burdening. So there arises a need for efficient mapping in order to ensure fairness in the allocation of these nodes.

Initially, our objective is to map this n CHs to m sink nodes such that there is no congestion at the sink. It is performed in three phases.

A. Congestion control at the sink nodes

Phase I

This phase involves detecting sink nodes which are in the range of a particular CH. A sink node S_j falls in the range of a CH_i, if and only if, $D(C_i, S_j) < T_{C_i}$ where $D(C_i, S_j)$ is the distance calculated between the CH_i and the sink node S_j and T_{C_i} is the transmission range of the CH_i. There might be so many sink nodes within the range of a particular CH. This is calculated for all nodes within the range of a CH.

Definition 1. *Coverage Factor*: Coverage Factor is defined as a function which maps from set of clusters, C, and set of sink nodes S, to a matrix. Mathematically, we have,

$$C : C \times S \rightarrow [0, 1]$$

$C(\cdot)$ is expressed as,

$$C(C_i, S_j) = \begin{cases} 0 & , D(C_i, S_j)) > T_{C_i} \\ 1 & , \text{otherwise} \end{cases} \tag{1}$$

Phase II

This phase involves the computation of individual preferences of a given CH for a given set of sink nodes. Here, the factors that we have considered are priority of the data, energy of the nodes, and volume factor of the data from the CHs. The three factors are considered to measure the importance of a given cluster data and proportionate weights are assigned, accordingly.

Definition 2. *Priority Factor*: Priority Factor PF is the weight determining the priority of data.

$$PF = \frac{(P_{act} - P_{avg})}{P_{act}} \tag{2}$$

where, P_{act} is the priority of the data to be sent by the node and P_{avg} is the average priority of the data.

Definition 3. *Energy Factor*: Energy Factor (EF) has an effect when it is very high indicating that its energy is drained and has to be given priority over other clusters.

$$EF = \frac{(E_{act} - E_{cur})}{E_{act}} \tag{3}$$

where E_{act} is the is the initial energy of the node and E_{cur} is the current energy of the node.

Definition 4. *Volume Factor*: Volume Factor is the measure of the extent of deviation of a particular CH from the average rate or volume of data from the other CHs.

$$VF = \frac{(V_{act} - V_{cur})}{V_{act}} \tag{4}$$

where V_{act} is the rate of the current CH and V_{avg} is the average rate of other CH.

Calculation of Individual Preferences

The order of individual preferences of sinks by the CHs is based on $P(C_i, S_j)$ where,

$$P(C_i, S_j) = U(C_i, S_j) \times C(C_i, S_j) \times P(S_j) \tag{5}$$

and $P(C_i, S_j)$ is the preference of a CH C_i given to a sink node S_j.

$U(C_i, S_j)$ is the utility function and is calculated as discussed in [11]. In the calculation of $U(C_i, S_j)$ we include the deviation of the mean of *PF*, *EF*, and *VF* from the normal data. Thus, the values obtained are given proportionate weights based on the energy, priority and volume of the data. $C(C_i, S_j)$ is the coverage factor and $P(S_j)$ is the packet service ratio of sink node S_i. Here, $P(S_j)$ is included in the computation because a particular sink node may be selected always by all the clusters resulting in congestion. Because of this packet service ratio the value of $P(C_i, S_j)$ is lessened as $P(S_j) < 1$ in case of congestion resulting in the change of individual preferences. After obtaining the preferences of every node, we obtain a matrix $P_{net}[1..n][1..m]$ for the entire network.

A preference ordering R_{S_i} for a particular sink S_i is the set of preference values of the different CHs of S_i, i.e.,

$$R_{S_i} = \{P_{C_1,S_i}, P_{C_2,S_i}, ..., P_{C_n,S_i}\} \tag{6}$$

A preference profile *P* is the set of potential preferences expressed as, $P = \{R_{S_1}, R_{S_2}, ..., R_{S_n}\}$.

Phase III

This phase discusses the social choice aggregation. Once the preference profile is established, we compute the Social Aggregation Function (SAF) and Social Choice Function (SCF). The SAF is defined as a mapping from preference domain to a mapping matrix M, $M[i][j]$ denotes the allocation of the j^{th} CH to sink S_i. The SAF, $F(\cdot)$, is mathematically expressed as:

$$F(P) = F(R_{S_1}, R_{S_2}, ..., R_{S_n}) = M \tag{7}$$

The SCF is denoted by a mapping $f : P \times S \rightarrow C$, i.e., given a preference profile and a particular sink, a particular CH is selected as the winner CH and is denoted by C_{win}. C_{win} is mapped to the sink node based on the choice of the society. $f()$ is expressed as,

$$f(R_{S_i}) = C_{win} \tag{8}$$

For the selection of a fair winner we use Borda's Count Method as discussed in [12]. This process is repeated for all the CHs till they are assigned to some sink nodes. This ensures fair distribution of the sink nodes to all the clusters satisfying the constraints.

B. Congestion control at the cloud gateways

Phase I

This phase involves detecting the cloud gateways which are in the range of a particular sink node. A cloud gateway G_j falls in the range of S_i if and only if $D(S_i, G_j) < T_{S_i}$ where $D(S_i, G_j)$ is the distance calculated between the sink node S_i and the cloud gateway G_j and T_{S_i} being the transmission range of the sink node S_i.

Definition 5. *Proximity*: Proximity determines the distance of cloud gateway from a sink node. Here, we assume that sink nodes are static and then calculate the distance between sink nodes and all gateway nodes. We assume the co-ordinates of sink nodes S_i as (S_{i_x}, S_{i_y}) and a gateway node G_j as (G_{j_x}, G_{j_y}). The distance between these two nodes is calculated as

$$D(S_i, G_j) = \sqrt{(G_{j_x}^2 - S_{i_x}^2) + (G_{j_y}^2 - S_{i_y}^2)} \tag{9}$$

Phase II

This phase involves the computation of individual preferences of a given sink node for a given set of cloud gateways. We consider the priority of the data, distance between the sink nodes and cloud gateways, and load of the cloud gateways. Priority factor can be calculated here in a similar fashion as stated in Equation 2. Distance between the nodes is calculated as stated in Equation 9.

Definition 6. *Load Factor*: Load Factor LF is used to regulate the flow control of the data there by reducing node level congestion. Load Factor LF is calculated as

$$LF = \frac{R_{out}}{R_{in}} \tag{10}$$

where, R_{out} is the output data rate from the cloud gateway and R_{in} is the input data rate in to the gateway.

If LF <1, it is intuitive that R_{out} <R_{in} i.e., output rate is less than input rate which is a determining factor for collision.

Calculation of Individual Preferences

The order of individual preferences of cloud gateways by the sink nodes is based on $P(S_i, G_j)$ where,

$$P(S_i, G_j) = U(S_i, G_j) \times LF \tag{11}$$

and $P(S_i, G_j)$ is the preference of a cluster S_i given to a sink node G_j and $U(S_i, G_j)$ is the utility value of a given sink-gateway pair and is calculated as,

$$U(S_i, G_j) = \frac{A}{D(S_i, G_j)} + B \times PF \tag{12}$$

where $D(S_i, G_j)$ is the distance between sink node and the cloud gateway, PF is the priority factor of the sink data, and A and B are constants. Inclusion of LF in preference calculation results in fair assignment of weights by the sink node to the cloud gateway.

A preference ordering R_{G_i} for a particular cloud gateway G_i is the set of preference values of the different sink nodes cast for S_i, i.e.,

$$R_{G_i} = \{P_{S_1,G_i}, P_{S_2,G_i}, ..., P_{S_n,G_i}\} \tag{13}$$

A preference profile *P* is the set of potential preferences expressed as:

$$P = \{R_{G_1}, R_{G_2}, ..., R_{G_n}\} \tag{14}$$

Phase III

The SAF is defined as a mapping from preference domain to a mapping matrix M, $M[i][j]$ denotes the allocation of the j^{th} sink node S_j to cloud gateway G_i. The SAF, $F(\cdot)$, is mathematically expressed as:

$$F(P) = F(R_{G_1}, G_{S_2}, ..., R_{G_n}) = M \tag{15}$$

The SCF is denoted by a mapping $f : P \times G \rightarrow S$ i.e., given a preference profile and a particular gateway, a particular sink node is selected as the winner and is denoted by S_{win}. Based on the choice of the society, S_{win} is mapped to the cloud gateway. $f()$ is expressed as,

$$f(R_{G_i}) = S_{win} \tag{16}$$

Using Borda's Count Method [12], we assign the sink nodes to the cloud gateways.

IV. Analytical Results

The basic network setup consists of some set of sink nodes and CHs. These nodes (both CHs as well as sink nodes) are randomly distributed in the network space. There can be many sink nodes which are in the transmission range of the same cluster. The basic network setup is shown in Figure 2.

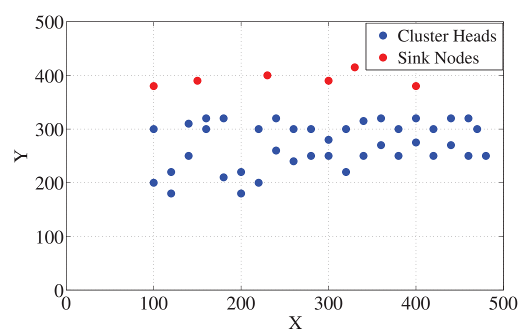

Figure 2: Network deployment scenario

Now, utility function of a CH is made through various parameters like energy, priority and volume of the data that is to be sent by the CH. The variation of utility function with mean of these parameters is shown in Figure 3.

As any one of the value PF, EF or VF increases for a particular CH, its utility increases, assuming the distance from CH to sink node as constant.

After, the utility function is calculated for each CH-sink pair, we calculate the preference of each of the CHs to all

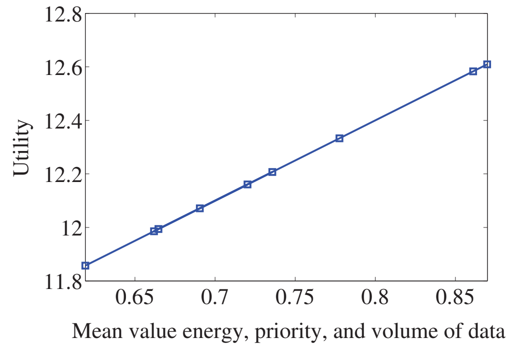

Figure 3: Variation of Utility with respect to mean of energy, priority and volume of data

Table I: Simulation Setup

Parameters	Values
Deployment Area	$500m \times 500m$
Deployment	Uniform, random
Number of sensors	120
Number of cluster heads	40
Number of sink nodes	6
Number of cloud gateways	3
Number of data centers	3
Average Priority of Data	5
Average Energy of Node	70 Joules
Average Volume Rate of Node	100 Kbps

sink nodes. The preference assigned is based on the coverage factor and utility function that is calculated. Preference of CHs to various sink nodes can be depicted as shown in Figure 4.

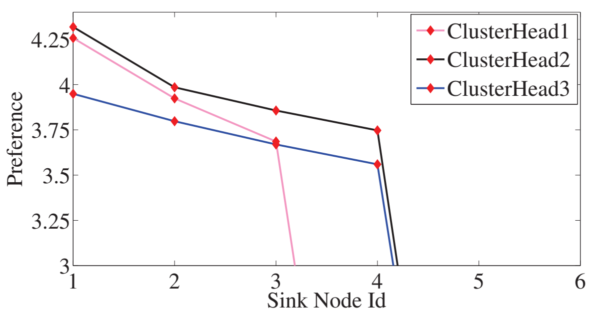

Figure 4: Preference of a Cluster Node for all sink nodes

As mentioned earlier, in order to ensure fairness among the allocation of sink nodes to cluster nodes, we include packet service ratio in calculating preferences. A particular sink node acknowledges its cluster about the load on that node. Thus, sink node 1 in the below example communicates to the CHs about its packet service ratio. As it is less than 1, all the CHs preference to that particular sink node is lessened. Thus, we can see the decline in the preference to the sink node 1 because of its packet service ratio as shown in Figure 5.

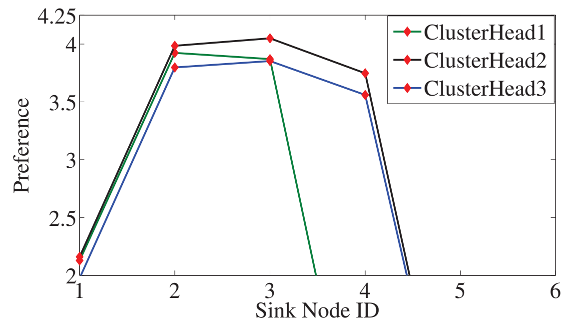

Figure 5: Preference of a Cluster Node for all sink nodes with packet service ratio

Network setup for the mapping between sink nodes and cloud gateways is as shown in Figure 6. It consists of six sink nodes and three cloud gateways.

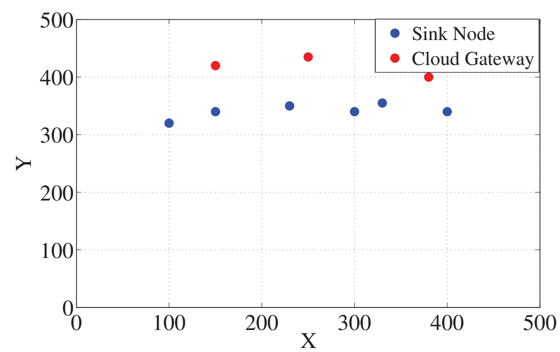

Figure 6: Network Setup for sink and gateway level mapping

Now, utility function of a sink node is made through various parameters like distance of that node to a gateway and priority of the data that is to be sent by that node. The variation of utility function with distance, keeping priority of the data constant, is shown in Figure 7.

In the next step, preference of a cloud gateway by a particular sink is calculated by making use of Load factor (LF) so that traffic is distributed and congestion is mitigated. The order of preferences by all sink nodes to all cloud gateways is shown in Figure 8.

As shown in Figure 8., the traffic is evenly distributed and channelized across all the cloud gateways without flooding a particular gateway. Thus, inclusion of load factor in the calculation of preferences helps us to mitigate congestion and reduce data loss.

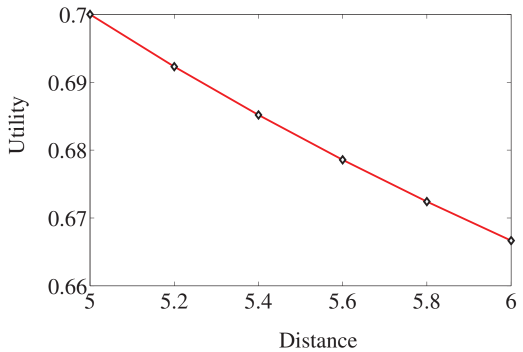

Figure 7: Variation of Utility with respect to distance

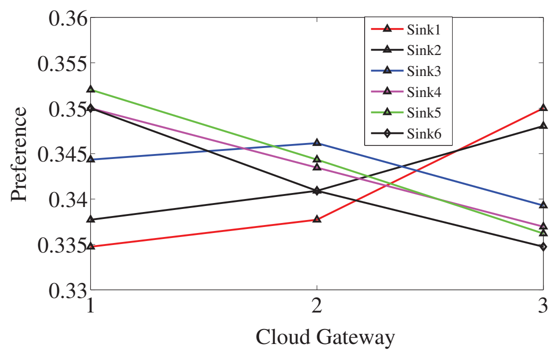

Figure 8: Preference of a Sink Node for all cloud gateways

V. Conclusion

The proposed solution ensures a "fair" allocation of cluster heads to sink nodes. It provides the best possible allocation of sink nodes to the cloud gateways, thereby, reducing congestion and data loss both at sink level and cloud gateway level. However, there can be challenges when CHs and sink nodes are mobile. So future work can be based on incorporating mobility to obtain a fair allocation even in case of mobile sensor nodes.

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