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Utility-Based Adaptation in Mission-oriented Wireless Sensor Networks

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Abstract—**This paper extends the distributed network utility maximization (NUM) framework to consider the case of resource sharing by multiple competing missions in a military-centric wireless sensor network (WSN) environment to consider three key new features observed in mission-centric WSN environments: i) the definition of a mission's utility as a joint function of data from multiple sensor sources ii) the consumption of each sensor's data by multiple receivers and iii) the multicast-tree based dissemination of each sensors data flow, using link-layer broadcasts to exploit the "wireless broadcast advantage" in data forwarding. We show how a receiver-centric, pricing-based, decentralized algorithm can ensure optimal and proportionally-fair rate allocation across the multiple missions, without requiring any coordination among independent missions (or sensors).**

I. INTRODUCTION

Data feeds from various sensors are expected to provide critical situational intelligence in a variety of future battlefield, homeland security, and disaster recovery environments. In many such applications, the sensor data is transported over a bandwidth-constrained multi-hop wireless network, for use by receivers in applications such as tracking, gunfire localization, etc. In this paper, we develop a Network Utility Maximization (**NUM**) based distributed rate control framework for sensor flows disseminated over a wireless sensor network (WSN).

The NUM problem and its distributed implementation have been extensively studied as a resource allocation mechanism for unicast flows in both wireline [2], [3], [4], [5] and ad hoc wireless networks [7], [8], [9], [11], [12], [6]. In a NUM-based approach for our mission-centric WSN environment we consider three new characteristics:

1) *Joint Utility Functions*, where an individual mission's utility is derived from *multiple sensor sources*.
2) *Multiple Heterogeneous Consumers of a Sensor Flow*, where each sensor broadcasts data to multiple missions as multicast flows.
3) *High Mission Variability*, because of which the NUM algorithm must provide *fast convergence*.

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II. NUM OPTIMIZATION FOR THE "JOINT UTILITY" WSN MODEL

We now consider the new environment of mission-based WSNs, where each mission's utility is a joint function of the rate from multiple sensors. Let the i^{th} mission be denoted as m_i, let M be the total set of missions, and S the total set of sensors. Let us denote the utility of the m^{th} mission as $U_m(X_m)$, where X_m represents the S-dimensional vector of rates associated with the set of sensors S (i.e., let $X_m[i]$ be the transmission rate of the i^{th} sensor s_i and $X_m[i] = 0$ if sensor s_i is not a source for mission m). Furthermore, for any mission m, let $set(m)$ be the set of sensors that are sources for m (i.e., contribute to the utility $U_m(.)$); conversely, for any sensor s, let $Miss(s)$ denote the set of missions subscribing to this sensor's data.

The problem of adaptive rate control in such a WSN may then be expressed by the $SENSOR$ problem:

$SENSOR(U, L)$:

$$\text{maximize} \sum_{m\in M} U_m(X_m) \qquad (1)$$

$$\text{subject to} \sum_{\forall(k,s)\in l} \frac{x_s}{c_{k,s}} \leq 1, \ \ \forall clique, l \in L..$$

Similar to the optimization framework in [2], we decompose the $SENSOR$ optimization problem into two subproblems $SINK$ and $NETWORK$, as shown below, by introducing a pricing scheme and show that solving these two problems independently solves a relaxation of the $SENSOR$ problem.

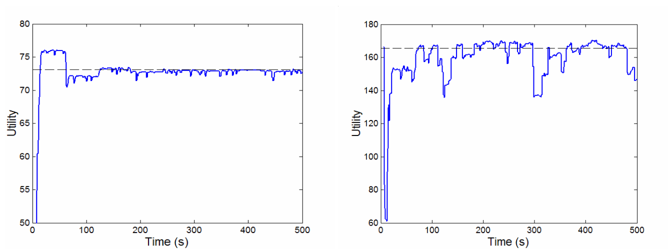
Suppose, a sink (mission) m is charged at a rate, λ_{ms}, for receiving a rate of x_s from sensor s. The sink m pays an amount w_{ms} per unit time, where $w_{ms} = \lambda_{ms} * x_s$. Thus w_{ms} can be interpreted as the 'willingness to pay'. Then the utility maximization problem for a *sink* m becomes:

$SINK_m(U_m; \lambda_m)$**:**

$$\text{maximize } U_m(\frac{\bar{w_m}}{\bar{\lambda_m}}) - (\sum_{s\in set(m)} w_{ms}) \text{ over} w_{ms} > 0 \qquad (2)$$

where $\bar{w_m}$ is a vector of w_{ms}, $\bar{\lambda_m}$ is a vector of λ_{ms} and element-wise division of $\bar{w_m}$ by $\bar{\lambda_m}$ is assumed.

Similarly, the $NETWORK$ problem becomes:



(a) $N = 20$ (5 sinks and 12 sources) (b) $N = 50$ (10 sinks and 30 sources)

Fig. 1: Utility of networks with different size.

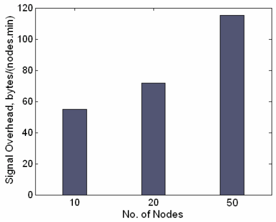


Fig. 2: Total packet overhead/node/minute (bytes) vs. network size

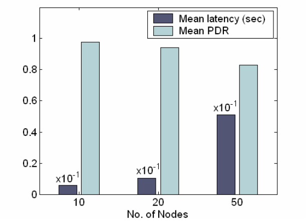


Fig. 3: Average packet delivery ratio (PDR) and latency vs. network size.

$NETWORK(L; w)$:

$$\begin{aligned} &\text{maximize} && \textstyle\sum_{s\in S}\sum_{m\in M} w_{ms} log(x_s); && (3)\\ &\text{subject to} && \textstyle\sum_{\forall(k,s)\in l} \frac{x_s}{c_{k,s}} \le 1, \text{ for each clique } l \in L, \end{aligned}$$

over $x_s \geq 0$.

The corresponding gradient ascent algorithm can be derived to be:

$$\frac{d}{dt}x_{s1}(t) = \kappa\Big(\sum_{m\in Miss(s1)} w_{ms1}(t) - x_{s1}(t) * \sum_{\forall l\in flow(s1)} \mu_l(t) * \sum_{\forall(k,s1)\in l} \frac{1}{c_{k,s1}}\Big) \quad (4)$$

where $\mu_l(t)$, a clique's shadow cost is given by:

$$\mu_l(t) = p_l\Big(\sum_{\forall(k,s)\in l} \frac{x_s(t)}{c_{k,s}}\Big)\Big) = \Big(\sum_{\forall(k,s)\in l} \frac{x_s(t)}{c_{k,s}} - 1 + \epsilon\Big)^+/\Delta \quad (5)$$

where Δ is a constant. In addition, each sink (mission) adapts its 'willingness to pay' for sensor s according to the equation:

$$w_{ms}(t) = x_s(t)\frac{\partial U_m}{\partial x_s} \quad (6)$$

We can show that the unique solution to the Equations 4 and 6 provides a decentralized, optimal solution to a relaxation of the problem $SENSOR(U, L)$ defined by Equation 1.

III. SIMULATION-BASED PERFORMANCE EVALUATION

We simulated our protocol using the Qualnet [13] discrete-event simulator. The actual transmissions of data packets are based on the distributed IEEE 802.11b MAC. These simulations *use network topologies generated according to a random, uniform distribution.*

A. Utility Variation with Time

Fig. 1 shows the variation in the total network utility with time, for two different values of N (the size of the network) equal to $\{20, 50\}$. We observe that the WSN-NUM protocol drives the network utility towards the optimal value.

B. Observed Overheads and QoS Metrics

Fig. 2 shows the signaling overhead involved. This includes the messages exchanged initially for local conflict graph construction and the periodic air-time exchanges performed once every minute. We can see that the additional signaling required in our protocol takes up only a few bytes per minute at a node. It is also important to study the actual packet-level QoS metrics observed by the receiving nodes. Fig 3 shows the average end-to-end latency and packet delivery ratios, as the network size N is varied.

IV. CONCLUSIONS AND FUTURE WORK

We developed and simulated a distributed optimization technique for resource sharing in mission-oriented WSNs, which is characterized by joint-utility functions and multicast dissemination of sensor data. We have provided further details about this work including methods to improve the speed of convergence in [14]. In future, we shall extend the NUM framework to capture the notion of mission *priorities*.

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