Ad hoc sensor network topology design for distributed fusion: A mathematical programming approach

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Abstract – *A distributed sensing/fusion network consists of more than one (spatially) separated sensors, each with possibly different characteristics and not all of them sensing the same environment. Due to their vast applicability, there has been a flurry of recent activity in the area of network design with respect to distributed sensing/fusion. Issues involved in the design of efficient networks include sensor mobility, reliability of links and capacity.*

This work builds on the Dynamic Expected Coverage Model proposed earlier and incorporates the issue of bandwidth capacity in the model. A Mixed Integer Linear Programming (MILP) formulation is proposed that includes first order preferential assignment with coverage and relocation of sensors. A modified column generation (CG) heuristic is developed for this problem. Computational results indicate that CG performs faster than standard commercial solvers and the typical optimality gap for large size problems is less than 10%.

Keywords: Wireless *ad hoc* networks, military applications, maximal expected coverage

1 Introduction

Recent advances in micro-electronic mechanical systems and wireless communication enables low cost, low power, multi-functional wireless sensors to collaborate sensing tasks. These sensors, capable of sensing, processing data, and short range communication, form *ad hoc* networks to deliver aggregate information from geographically diverse areas, hence achieving tasks that may never be achievable using a single, perhaps powerful, sensor. An *ad hoc* network is a self-organizing multi-hop wireless network, which relies neither on fixed infrastructure nor on predetermined connectivity. This property enables rapid deployment without precise prior knowledge of the coverage area of interest - hence serves well for situations lacking fixed infrastructure or high risk, e.g., in military communications, disaster management, law enforcement, etc. Furthermore, continuous adaptation of sensing and communication topology allows to achieve efficient coverage and data fusion, even with environmental changes/threats or sensor failures. The efficiency is intrinsically important for *ad hoc* sensor networks, especially when the resources (network bandwidth or overall sensor energy) are limited and no easy recharging or re-deployment may be performed in inaccessible terrains. The question therefore is how should networked sensors collaborate to collect as much data as possible while utilizing very few resources?

Fusion of data from multiple sensors (e.g., radars on the ground and sonars under water) facilitates a better judgment of the scenario since we get multiple inputs to verify the authenticity of the information – see, e.g., [1]. The scenario that we are referring to is a dynamic battlefield in which enemy movement is occurring and targets are being tracked. Data from multiple sensors is being fused so as to yield better estimates for target tracks. In such a circumstance both the sensors and the fusion bed (e.g., an Airborne Warning and Control System (AWACS)) are mobile. Such a network has to rely on wireless transfer of information in an *ad hoc* network. The focus of our work is to provide a robust architecture for performing fusion in a hostile environment, where communication links are prone to enemy attack. We assume that sensor movement patterns are known. Our goal is to find the best locations for clusterheads (fusion nodes), for each time period over the planning horizon. We tradeoff the need to provide maximal expected coverage in a hostile environment versus preferential assignment and the cost of frequent relocation of clusterheads. *The role of a clusterhead* in the fusion environment is to fuse sensor reports or tracks from the sensors that 1-hop away and are assigned to it. A clusterhead could also serve as a communication gateway when fusion is conducted across clusterheads.

It is important to emphasize that ours is a strategic model which will help plan a robust communication scheme over a mission duration. The model deals with communication issues such as assignment of specific channels to a particular communication link. It also incorporates bandwidth capacity issue. It focuses on the development of a plan to strategically relocate clusterhead locations so as to maximize the overall efficiency of the communication system – which includes maximizing the expected coverage of sensors and minimizing the overhead cost of changing clusterhead locations.

2 Literature Review

Ad hoc networking is now an important part of mobile communication and computing. An *ad hoc* network is a self or-

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ganizing multi-hop wireless network that can be rapidly deployed. It works completely on a decentralized system due to lack of fixed infrastructure. Network topology in *ad hoc* networks are either hierarchical or flat. Ramanathan and Steenstrup [2] presented Multimedia support for Mobile Wireless Networks (MMWN) based on hierarchical structure. Haas and Tabrizi [3] discussed the flat architecture and its advantages over the hierarchical architecture. On the other hand, Evans, Scachez and Minden [4] introduced the Highly Dynamic Multi-hop wireless network (HDnet) and figured out that hierarchical networks are preferred over flat in terms of some aspects such as scalability, location management, etc.

Location Management is the set of mechanisms used to determine where a sensor is with respect to the network infrastructure, which is a key issue in *ad hoc* communication. It provides a time-varying mapping between the sensor identifier and address. A number of location management strategies have been proposed. Sharony [5] partitioned a mobile network into logically independent subnetworks. Network nodes are members of physical and virtual subnets and their addresses are based on their current subnet affiliation. Pei and Gerla [6] provides a mobility management for Hierarchical State Routing (HSR) protocol, where the *ad hoc* mobile wireless network is hierarchically organized into a multilevel clustering structure. The key feature is use of the notion of logical subnets to handle the mobility. The problem with these strategies is that they do not exploit hierarchy at the network layer to reduce the frequency of location registration to distant location servers, that is, all events triggering a location update. Li *et al.* [7] proposed Grid Location Service (GLS) which relies on a grid-based geographic hierarchy overlaying the network area. Each node has a set of nodes functioning as location servers and maintains a table of immediate neighbors as well as each neighbor's neighbors.

In *ad hoc* networks the routing has to be determined dynamically and the literature for routing protocols is divided into Proactive or Table Driven Routing Protocol, Reactive or On-Demand Routing Protocol and Hybird Protocol, the last being a combination of the first two. In a proactive protocol, the route between each pair of nodes is continuously maintained in a tabular format, the delay in determining the route is minimal, but maintaining the table is a costly affair. Some of the protocols cited in the literature are: Destination-sequenced Distance-Vector Routing (DSDV) [8], Clusterhead Gateway Switch Routing (CGSR) [9], and Wireless Routing Protocol (WRP) [10]. In a reactive protocol, routes are determined on a needs basis; examples are *Ad Hoc* On-Demand Distance Vector Routing (AODV) [11], Dynamic Source Routing (DSR) [12], Associativity Based Routing (ABR) [13] and the Temporally Ordered Routing Algorithm (TORA) [14]. Hybrid protocols combine the advantages of both reactive and proactive protocols. Haas [15] proposed Zone Routing Protocol (ZRP), a hybrid protocol based on the notion of routing zones. In this protocol, each node pro-actively determines the routes between itself and nodes within its routing zone. Thus whenever a demand arises, with little effort the route can be determined among the nodes not in the routing zone.

Clustering of nodes in *ad hoc* networks are done in order to use the wireless resources efficiently by reducing congestion and for proper location and routing management. Since the clusterhead selection is an NP-hard problem ([16]), most existing solutions available are based on heuristic approaches. Most of the clustering algorithms described in literature assume that the links between nodes within a cluster are reliable and data can be communicated between them at all times. The fusion process demands a highly reliable and stable network architecture for collecting and processing data from all the mobile sensors. In this paper a mathematical programming based approach is adopted for dynamic clustering.

The math programming approach that we use in this paper is based on a variation of a maximal expected covering location model due to Daskin [17]. We therefore review relevant literature on covering location problems. Toregas *et al.* [18] modeled the location of emergency service facilities as a Set Covering Location Problem (SCLP) where the objective is to cover all demand with the least number of facilities. Church and ReVelle[19] proposed the Maximal Covering Location Problem (MCLP) with the objective to cover maximum demand with a restricted number of facilities. As a surrogate to modeling server unavailability, Hogan and Revelle [20] introduced the concept of backup coverage in the context of SCLP and MCLP, and Batta and Mannur [21] reconsidered the SCLP and the MCLP with multiple units required by the demand nodes. Berman and Krass [22] introduced a generalized version of MCLP (GMCLP) with partial coverage of demand nodes. Chapman and White [23] modeled the probabilistic version of SCLP ensuring that each node is served by a specified reliability level α. Daskin [17] introduced a variant of the MCLP that considers the possibility that facilities may be unable to respond to demand at all times. The resultant model was labeled as MEXCLP (Maximum Expected Covering Location Problem). In a later paper, Batta *et al.* [24] attempted to relax three of the assumptions made in the MEXCLP model. Other papers that have attempted to enhance the basic MEXCLP model are those by [25, 26, 27, 28, 29].

Patel, Batta and Nagi [30] extend MEXCLP model proposed in [17] by modeling the problem as a covering location problem with the objective of maximizing the expected demand covered by locating a given number of cluster heads. However, even though modeling it as a communications network, one important aspect was not considered - *bandwidth*. The importance of capacity in communication network, specially for large scale distributed sensing networks cannot be over-emphasized. We extend the Dynamic MEXCLP model due to [30] by incorporating capacity constraints. We refer to our model as Capacitated Dynamic MEXCLP.

2.1 Problem Formulation

The *Capacitated Dynamic MEXCLP* is a strategic model. The model assumes that the cluster heads are completely reliable while all links have (identical) steady-state probability of failure. Sensors are mobile with known velocity vectors. The time horizon is divided into equal time periods and relocation of cluster heads takes place at the beginning of each time period. Cluster heads are identical in all respects. The data transmission is assumed to be negligible and is not transmitted in packets.

In order to incorporate the capacity constraint, each sensor needs to be assigned to one of the cluster heads that is "covering" it. However, we still have link failure probabilities and correspondingly, need multiple coverage of sensors. Thus the trade off is between multiple coverage and preferential assignment on one side and relocation cost on the other. We present two different formulations based on the way in which capacity constraints are applied. In the first formulation, capacity constraint is applied for each time period while in the second, it is applied for the entire time horizon. Thus the second one can be viewed as a relaxed version of the first.

Parameters:

- Δ = set of potential clusterhead locations.
- Θ = set of sensors.
- n = maximum number of clusterheads to be located.
- T = maximum number of time periods in the horizon under consideration.
- U = the distance beyond which a sensor is considered "uncovered".
- D_{ikt} = distance between potential facility location i and demand node k at time t.
- d_k = demand per period of node k.
- p = probability of a link failure per period (between any facility and demand node). ($0 < p < 1$)
- $r_{ikt} = \begin{cases} 1, \text{ if } D_{ikt} < U. \\ 0 \text{ otherwise.} \end{cases}$
- c_{ik} = value of preference of assignment of sensor k to cluster head location i
- Q_{it} = capacity of cluster head location i during time period t
- C = cost per unit change in the number of facilities at any location i (one-half of relocation cost).

Decision Variables

$$x_{it} = \begin{cases} 1, \text{ if a clusterhead is placed at location } i \text{ at time } t, \\ 0 \text{ otherwise.} \end{cases}$$

$$z_{ikt} = \begin{cases} 1, \text{ if sensor } k \text{ is assigned to cluster head } i \\ \quad \text{during time period } t, \\ 0 \text{ otherwise.} \end{cases}$$

$$y_{jkt} = \begin{cases} 1, \text{ if sensor } k \text{ is covered by at least } j \\ \quad \text{clusterheads at time } t, \\ 0 \text{ otherwise.} \end{cases}$$

w_{it} = positive difference in the number of clusterheads at location i between time $t-1$ and time t.

Formulation:

(P) Maximize

$$\sum_{t=0}^{T}\sum_{k\in\Theta}\sum_{j=1}^{n}(1-p)p^{j-1}d_k y_{jkt} + \sum_{i\in\Delta}\sum_{k\in\Theta} c_{ik}z_{ikt} - \sum_{t=1}^{T}\sum_{i\in\Delta} Cw_{it},$$

subject to

$$\sum_{j=1}^{n} y_{jkt} - \sum_{i\in\Delta} r_{ikt}x_{it} \le 0 \quad \forall\, k = 1,\dots,|\Theta|, t = 0,\dots,T \tag{1}$$

$$\sum_{i\in\Delta} x_{it} \le n \quad \forall\, t = 0,\dots,T \tag{2}$$

$$w_{it} \ge x_{it-1} - x_{it} \quad \forall\, i = 1,\dots,|\Delta|, t = 1,\dots,T \tag{3}$$

$$w_{it} \ge x_{it} - x_{it-1} \quad \forall\, i = 1,\dots,|\Delta|, t = 1,\dots,T \tag{4}$$

$$z_{ikt} \le r_{ikt}x_{it},\ \forall i = 1,\dots,|\Delta|, k = 1,\dots,|\Theta|, t = 0,\dots,T \tag{5}$$

$$\sum_{i\in\Delta} z_{ikt} \le 1 \quad \forall\, k = 1,\dots,|\Theta|, t = 0,\dots,T \tag{6}$$

$$\sum_{k\in\Theta} d_k z_{ikt} \le Q_{it} \quad \forall\, i = 1,\dots,|\Delta|, t = 0,\dots,T \tag{7}$$

$$x_{it} \in \{0,1\} \quad \forall\, i = 1,\dots,|\Delta|, t = 0,\dots,T \tag{8}$$

$$w_{it} \ge 0 \quad \forall\, i = 1,\dots,|\Delta|, t = 1,\dots,T \tag{9}$$

$$y_{jkt} \le 1\ \forall j = 1,\dots,n, k = 1,\dots,|\Theta|, t = 0,\dots,T \tag{10}$$

$$z_{ikt} \in \{0,1\},\ \forall\, i = 1,\dots,|\Delta|, k = 1,\dots,|\Theta|, t = 0,\dots,T \tag{11}$$

The objective function maximizes demand covered and preferential assignment while allowing for relocation of clusterheads over a time horizon. If node k is covered by m clusterheads at time t, Constraint (1) assigns each of the variables $y_{1kt}, y_{2kt}, \dots, y_{mkt}$ a value of 1 since the objective function is a maximization function containing the term y_{jkt}. Constraint (2) restricts the maximum number of clusterheads to be located to n for any time t. Constraints (3) and (4) determine the positive difference between the number of clusterheads located at location i between time $t-1$ and t. Constraint (5) ensures that sensor k is assigned to cluster head location i only if location i is occupied by a cluster head and sensor k can be covered from location i. Constraint (6) ensures that a sensor is assigned to only one cluster head during a time period. Constraint (7) is capacity constraint for each cluster head location for each time period. Constraints (8), (9),(10) and (11) are binary constraints.

An alternative formulation of (P) can also be given. The variables and their indices for this formulation are same as (P) except for Q_{it}, which is replaced by Q_i representing the capacity of cluster head location i over the entire time horizon (note again that all the cluster heads are assumed to be identical). It can easily be shown that for an optimal solution of (P) the w_{it} variables will take on $0-1$ binary values. Furthermore, for an optimal solution of (P) the y_{jkt} variables will also take on $0-1$ binary values. This is because the term $\sum_{i\in\Delta} R_{ikt}x_{it}$ will be integral since R_{ikt} are $0-1$ binary constants and variables x_{it} assume only $0-1$ binary values. The z_{ikt} variables need not take $0-1$ values unless defined to do so. It might also be noted here that the preferential assignment is an attempt to capture capacity restrictions and is not completely accurate. Because it only considers first order link failures and does not take subsequent assignments into consideration. In other words, if the link between a sensor and its most preferred cluster head location breaks down, subsequent link assignments are not accounted for.

3 Column Generation Heuristic

Column generation (CG) heuristic is a widely used technique to solve large-scale optimization problems in context of scheduling, set-partitioning, and vehicle routing. It is typically used in a multi-period model when the number of solutions available for each period is very large. For example, in vehicle routing the available routes for each vehicle are combinatorially large. The reader is referred to the following papers for a description of the technique in a variety of different applications: [31] solve the fleet routing and scheduling problem using a CG based approach. [32] solve set-partitioning problem encountered in the context of traffic assignment in satellite communication using a CG heuristic. [33] adopt a CG heuristic to develop conflict-free routes on a bi-directional network for automated guided vehicles. [34] solve a linear multi-commodity flow problem using an iterative partial pricing scheme that is motivated by the CG approach of Dantzig-Wolfe decomposition.

CG is an iterative scheme where a sub-problem generates feasible solutions and a master problem evaluates and selects these feasible solutions. The sub-problems in our scheme are time separable and generate the optimal clusterhead assignment for each time period (based on the current dual multipliers). The master problem picks the best solution for each time period. We define some additional parameters and variables used in the master problem and sub-problem for the CG approach:

F_t = index set representing the available solutions for time t.

X_{sit} = value of x_{it} if solution $s \in F_t$ is selected at time t.

Y_{sjkt} = value of y_{jkt} if solution s is selected at time t.

The decision variables of the problem are:

$$f_{st} = \begin{cases} 1 \text{ if solution } s \in F_t \text{ is selected at time } t, \\ 0 \text{ otherwise.} \end{cases}$$

3.1 Master Problem

The master problem evaluates the set of solutions available for each time period and selects one for each period such that the objective value is maximized. It is stated as follows:

Maximize

$$\sum_{t=0}^{T}\sum_{k\in\Theta}\sum_{j=1}^{n}\sum_{s\in F_t}(1-p)p^{j-1}d_k f_{st} y_{sjkt} + \sum_{t=0}^{T}\sum_{i\in\Delta}\sum_{k\in\Theta}\sum_{s\in F_t} c_{ik} z_{sikt} f_{st} - \sum_{t=1}^{T}\sum_{i\in\Delta} C w_{it}$$

subject to

$$-w_{it} + \sum_{s\in F_{t-1}} f_{st-1}x_{sit-1} - \sum_{s\in F_t} f_{st}x_{sit} \le 0, \quad \forall i = 1,\ldots,|\Delta|, t = 1,\ldots,T \tag{12}$$

$$-w_{it} + \sum_{s\in F_t} f_{st}x_{sit} - \sum_{s\in F_{t-1}} f_{st-1}x_{sit-1} \le 0, \quad \forall i = 1,\ldots,|\Delta|, t = 1,\ldots,T \tag{13}$$

$$\sum_{s\in F_t} f_{st} = 1, \quad \forall \ t = 0,\ldots,T \tag{14}$$

$$f_{st} \in \{0,1\}, \quad \forall \quad s, t = 0,\ldots,T \tag{15}$$

$$w_{it} \ge 0, \forall i = 1,\ldots,|\Delta|, t = 1,\ldots,T \tag{16}$$

The master problem is solved as relaxed linear program with no binary constraint on the variables. This is referred to as the relaxed master problem (RMP). Constraints (12) and (13) are same as in (P) except that we have variable f_{st} replacing x_{it} and y_{jkt}, whereas x_{it} and y_{jkt} are constants. Variable f_{st} represents a feasible solutions (column). Let $\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}$ be the dual multipliers corresponding to constraints (12), (13) and (14), respectively. The sub-problem generates the feasible solutions using these dual multipliers.

3.2 Sub-problem for Period t

The objective of the sub-problem is precisely the reduced cost of an entering column to the master problem. The sub-problem is solved for each time period t separately. The sub-problem for time periods $t = 1$ to $t = T - 1$ is as follows:

(SP_t) Max.

$$\sum_{k\in\Theta}\sum_{j=1}^{n}(1-p)p^{j-1}d_k y_{jkt} + \sum_{i\in\Delta}[\beta_{it} - \beta_{it+1} - \gamma_{it} + \gamma_{it+1}]x_{it} + \sum_{i\in\Delta}\sum_{k\in\theta} c_{ik}z_{ikt} - \delta_t$$

subject to

$$\sum_{j=1}^{n} y_{jkt} - \sum_{i\in\Delta} r_{ikt}x_{it} \le 0 \quad \forall \quad k = 1,\ldots,|\Theta| \tag{17}$$

$$\sum_{i\in\Delta} x_{it} \le n, \qquad \forall t = 0,\ldots,T, \tag{18}$$

$$z_{ikt} \le r_{ikt}x_{it}, \forall i = 1,\ldots,|\Delta|, k = 1,\ldots,|\Theta|, \quad t = 0,\ldots,T, \tag{19}$$

$$\sum_{i\in\Delta} z_{ikt} \le 1 \qquad \forall \quad k = 1,\ldots,|\Theta|, t = 0,\ldots,T, \tag{20}$$

$$\sum_{k\in\Theta} d_k z_{ikt} \le Q_{it} \quad \forall \quad i = 1,\ldots,|\Delta|, t = 0,\ldots,T, \tag{21}$$

$$z_{ikt} \in \{0,1\}, \forall i = 1,\ldots,|\Delta|, k = 1,\ldots,|\Theta|, \quad t = 0,\ldots,T. \tag{22}$$

$$y_{jkt} \le 1, \quad \forall \quad j = 1,\ldots,n, k = 1,\ldots,|\Theta| \tag{23}$$

$$x_{it} \in \{0,1\}, \qquad \forall \qquad i = 1,\ldots,|\Delta| \tag{24}$$

Due the non-availability of the dual multipliers β and γ for t = 0 and t = T - 1, the objective function has a different form for these time periods.

For $t = 0$:

$$\sum_{k\in\Theta}\sum_{j=1}^{n}(1-p)p^{j-1}d_k y_{jkt} + \sum_{i\in\Delta}[-\beta_{it+1} - \gamma_{it+1}]x_{it} + \sum_{i\in\Delta}\sum_{k\in\theta} c_{ik}z_{ikt} - \delta_t$$

For $t = T$:

$$\sum_{k\in\Theta}\sum_{j=1}^{n}(1-p)p^{j-1}d_k y_{jkt} + \sum_{i\in\Delta}[\beta_{it} - \gamma_{it}]x_{it} + \sum_{i\in\Delta}\sum_{k\in\theta} c_{ik}z_{ikt} - \delta_t$$

The solution of sub-problem (SP_t) is a set of x_{it} and y_{jkt} values. These coefficient values are said to represent a solution f_{st}, which is added to the index set of solution F_t for period t in the master problem. If the sub-problem for every period t fails to produce a solution with strictly positive reduced cost, then the procedure terminates.

3.3 Initial Basic Feasible Solution

The Column Generation(CG) approach works in the feasible domain. The CG heuristic requires an initial basic feasible solution to start with. It starts with this solution and keeps on improving the objective function value by generating new solutions termed as "columns" and selecting the one that improves the objective function the most. The effectiveness of the CG approach is enhanced by the quality of the initial basic feasible solution. Hence it is important to develop a good heuristic for obtaining an initial basic feasible solution. [30] proposed Relocation and No-relocation heuristics for Dynamic MEXCLP. In our case we use the modified version of these two heuristics and start with two basic feasible solutions for each time period generated by the Modified Relocation Heuristic (MRH) and Modified No-Relocation Heuristic (MNRH). The modified versions differ from [30]: The demand covered by each potential is substituted by the sum of the demand covered and the preferred assignment for each potential location (refer [35] for details).

MRH is a greedy heuristic, which picks the best n locations, one at a time, for each time period. The heuristic takes into consideration the link failure probabilities and later adds relocation cost incurred in switching clusterheads locations in two successive time periods. MNRH is also a greedy heuristic in which the strategy is to place clusterheads at locations which cover maximum demand for all time periods assuming that relocation is not permitted. The heuristic also accounts for link failure probabilities in a similar manner to MRH, but does not reassign clusterheads.

Our results showed that in most randomly generated scenarios, the solution quality of the heuristics is good. However, particular examples can be contrived where each heuristic can perform very poorly (see [30]). We therefore use solutions from both MRH and MNRH simultaneously as the initial columns (feasible solutions) of the CG procedure.

3.4 Solution Approach

The solution approach adopted can be stated as follows. At each iteration we solve RMP and then solve the subproblems for time periods t=0 through t=T. The solutions with favorable reduced cost are simultaneously added to the master problem. Iterations are continued till the termination criterion is reached. We terminate CG iterations if none of the sub-problems give a solution of favorable reduced cost. In certain cases, the CG heuristic will keep on iterating with a very small increase in the objective function of the RMP. In such cases, other termination criterion can be utilized by a user: (i) a threshold time within which a solution is required, and (ii) a bound on the number of iterations.

At the end of CG heuristic RMP contains separate set of columns for each time period. At this stage we solve integer master problem (IMP) that attempts to choose exactly one column for each time period so as to minimize the total cost. Event hough this does not guarantee to provide optimal solution to the original problem (P), it still works well in practice (e.g.,[33]).

4 Computational Results

Based on the solution methodologies proposed in the previous section, we condcuted numerical studies for the Capacitated Dynamic MEXCLP. The software was implemented using C and CPLEX 7.1 callable library on an Intel Pentium IV processor based workstation with 1.7 GHz of speed, 512 MB RAM and running Windows 2000 operating system. We solve formulation (P) using CPLEX 7.1 MILP solver and also use the CG heuristic which was coded in C and used CPLEX 7.1 callable library. Test results show that the % gap between the LP relaxation of the (P) and the optimal solution is much wider for capacitated case. It was noted that increasing p increased the solution time for both CG and CPLEX. No significant trend was observed for most performance values with respect to varying M. But most of the performance indexes peaked around a value of M. The average plot of these performance measures with respect to M might tend to be concave downwards. Detailed computational results are shown in [35].

5 Summary

In this work, we presented a strategic model for communication network problem for distributed fusion that consist of finding optimal assignment of clusterheads for collecting data from sensors spread over a geographically dispersed area. We model the problem as a Capacitated Dynamic MEXCLP (generalization of Dynamic MEXCLP presented in [30]). The model incorporates issues of communication link failure, mobility of sensors and cluster heads, bandwidth capacity. A column generation heuristic is developed to solve Capacitated Dynamic MEXCLP. It was noted that addition of capacity constraints significantly increased the complexity of problem.

The model can be enhanced to include more realistic situations in a military context. The assumption that the sensor locations are known in advance for every time period can be relaxed to consider uncertainty of location with respect to time. Unique link failure probability assumption can be relaxed and time varying link failure probabilities can be used to find the dependencies and the ranges of these probabilities.

Acknowledgements

This research was performed under the sponsorship of NIMA and managed by Rosettex Technology and Ventures Group under Task Order # RTVGC-02-216-03-C-CR-2-001. The authors gratefully acknowledge their support.

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