Modeling Situational Awareness in Network Centric Systems

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ABSTRACT

Modeling Situation awareness (SA) in NCO/NCW environments is inherently challenging due to the complexity of the underlying network, highly dynamic nature of processes, and the need for real time analysis. In this paper, we present a performance model for SA using the Network Centric Operations Performance & Prediction (NCO-PP) framework, an established framework for analyzing and predicting performance of NCO/NCW networks. In this paper, we continue to formulate a realistic model that represents dynamism in both the information and network spaces and also their effects on each other. We validate our model via simulations that compare the performance of SA under various information sharing and filtering paradigms. We provide and define a number of relevant performance metrics for SA and show with experimental results that modeling the dynamism in the network lead to superior SA. We also show that the performance of the SA can be significantly improved with proactive resource allocation that takes into account the real time predictions of the future states of the network and the environment.
Keywords: Situation Awareness, Performance Modeling, Network Centric, Complex Networks, NCO Framework

1. INTRODUCTION

Network Centric Warfare (NCW)[1][2][4][6][8] is "the conduct of military operations using networked information systems"[1]. Network Centric Operations (NCO) is the application of NCW to a wide spectrum of operations from peace to crisis to war. It is called "Network Centric"[3] because the network and the information carried in the network is key to all aspects of the operations. Network Centric Operations have gained center stage in modern military and security organizations around the world. The NCO doctrine aims at effectively leveraging information in order to better coordinate the deployment and activities of various entities in highly dynamic conditions. NCO/NCW is facilitated by emergence of reliable and portable communication systems which has made it possible for even actors on the "edges", such as war-fighters, to quickly relay the situation on the ground to their superiors. Efficient sharing of information leads to a better understanding of the ground reality. The perception that each node has about the situation is termed as Situational Awareness (SA). SA includes information about the status of friendly and enemy forces, deployment of resources etc. Traditional models[10][11][15] in SA have concentrated on the cognitive/decision making aspects. Although these aspects are important, abstracting the characteristics of the underlying network is crucial for a realistic SA model in the NCO/NCW domain. Understanding the key networking factors in the modeling of Situational Awareness and how it affects other aspects such as decision making is a key concern in this paper.

NCO/NCW networks are typically complex with multiple technologies, working together in a conglomeration of sub-networks. SA process which depends on information getting to the right place at the right time is highly dependent on the underlying network. Conversely, the decision making/information sharing in turn depends on the dynamism in the network. Additionally, users actively change the configuration of the network based on requirements that have a ripple effect on the other aspects. As such, extreme and erratic network behavior is observed in NCO/NCW networks. Traditional frameworks are not broad enough to take all these aspects into account. Current network modeling methods which heavily favor average analysis[22][23] and heuristics[16][17] will fail to adequately model the real time processes in NCO/NCW network. A computational/simulation framework that mathematically abstracts the underlying functional mapping between the different aspects of the NCO/NCW network is required. One such framework is the Network Centric Operations Performance & Prediction (NCO-PP)[5], which is a flexible, interactive components based framework. Each of the components represents the various aspects of the NCO/NCW such as network architecture/hierarchy, network dynamism, metrics and analysis tools. By defining the functional mappings between

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these components, the framework models their interaction and in the process, gives a more realistic representation of the real time dynamism in the network. NCO-PP has plug-n-play features wherein modeling techniques can be introduced in a component quickly and without making changes to other components. Prediction and optimization schemes can also be incorporated in NCO-PP. All these properties of NCO-PP make this framework ideal for modeling the SA process in NCO/NCW network. In NCO-PP, we model SA by abstracting the network space and information space separately and defining interactions between these two layers. We will validate our model and certain hypotheses about the information sharing and resource allocation paradigms using meaningful experiments. In the next section, we will elaborate on the issues faced while modeling SA. This will be followed by the section describing our model in detail, followed by experimental validation of the model. We note that for brevity, a number of discussions, results, analysis, and other information may have been only briefly described in this paper. For a full discussion, please refer to [21].

2. ISSUES IN MODELING SITUATIONAL AWARENESS

Endsley[9] describes SA as "the perception of elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future". The three main aspects of SA is perception, comprehension and projection [9][11]. Perception is the first step during which situational entities such as objects, people and events are detected and monitored for changes in state or behavior. In the comprehension phase, information from various heterogeneous sources is integrated and its relevance to goals/objectives and to the overall "big picture" is gauged. In the projection stage, the future impact of the SA is gauged. These concepts of Situation Awareness are applied to diverse fields and specific models have been built for domains such as air traffic control[10], emergency response [12], public health system[13], homeland security[15] and many others. Although these models are interesting, they are limited by their relevance specific to their fields. Most of these models also do not take network characteristics into account, which can be a serious drawback in the NCO/NCW domain.

We now review some of the works that take network behavior into account in their models. Lu[16] derived an expression to determine maximum allowed delay over the network to keep position error estimates within bounds and perform analysis of the average SA age, using the speed of the mobile platforms and transmission failure probability. White[17], in addition to using traditional network metrics like end-to-end delay and throughput, defines some new metrics such as average end-to-end delay, message completion rate etc in their SA model. Manikopoulos[18] models information staleness for TCP and UDP protocols in a stock update application using average delay and packet delivery ratio metrics. The work described here are limited to only the perception aspect of SA. They are not generalized models that can be applied to other aspects of SA such as comprehension and projection. These models also do not take the dynamics of the environment into account. In short, current methods will not provide realistic models for NCO/NCW.

One of the challenges in modeling NCO/NCW networks is due to the presence of node and link heterogeneity. Some of the heterogeneity commonly observed are in the form of node functionality (sensor node, command node etc.), node mobility and communication technology used. The network is also dynamic and changing due to the nature of the nodes themselves or because of the environment. Since nodes are mobile, they may move in and out of groups and subnets, creating new virtual organizations and collaborations. The environment can be challenging with nodes coming under duress in the form of enemy fire or adverse weather conditions. In such cases, the nodes may temporarily fail or altogether be destroyed. Thus network heterogeneity and network dynamism are key factors that affect the information flow in the NCO/NCW networks. Network delay in the information created by the network can lead to inconsistencies in SA and nodes in the same subnet may end up having different Common Operating Picture(COP) or the big picture. This can jeopardize the decision making mechanism and lead to chaos. By leveraging information about the underlying network architecture and dynamism in our SA models, we can design novel information sharing paradigms resulting in better and faster SA. Modeling the network will also help us to proactively allocate resources and mitigate the adverse effects of network dynamism on SA. We will now describe how we abstract the details of the network architecture, heterogeneity and dynamism in our model and seamlessly meld it with the decision making aspects of the NCO/NCW.

3. MODELING SITUATIONAL AWARENESS WITHIN NCO-PP

In this paper, we formulate a performance model for Situational Awareness (SA) for NCO/NCW networks within the NCO-PP framework. The NCO-PP framework consists of 4 components: 1) Network Representation Component(NRC) 2) Performance Module Component(PMC) 3)Performance Tools Suite Component(PTSC) 4) Sub-module Interaction

Component (SIC). For more details about components of NCO-PP, refer to [5]. We model the various aspects and factors involved in the SA process in the different components of NCO-PP. The underlying functional mapping between the components helps in modeling their interaction and their influence on each other. To begin with, the network attributes such as architecture, hierarchy and node properties are modeled in the NRC. Specifically, we use graph theoretic concepts to represent the network in NRC. Additionally, the network graph in NRC has additional attributes to represent the flow of information. Since changes in the network graph will automatically alter the information flow, NRC is able to represent the interaction between the network and information layers. With NRC, we can model the conditions of the network at a static snapshot in time. To represent the dynamism in NCO/NCW networks, we define mathematical functions within PMC for mapping the transitions between successive snapshots of the network represented by the NRCs. In order to conduct performance analysis with our model, we define metrics in the PTSC module. Due to the plug-n-play nature of NCO-PP, the labels/attributes in the NRC, the functional mapping in the PMC and the metrics used in the PTSC are not fixed. In fact, each component can be modified independently of other components. Although we are able to model and analyze the SA performance using NRC+PMC+PTSC, the SIC component in NCO-PP helps in utilizing this information in order to come with recommendations for optimal behavior.

NCO-PP is a generic framework which allows for wide ranging models representing different aspects of NCO/NCW to work together. And by modeling SA within NCO-PP, we retain our model's ability to extend to various scenarios, conditions and incorporate different modeling tools and techniques. As a preliminary step towards validating our model, we provide specifics of techniques, representations and algorithms that may be used within our model as an initial realistic implementation of the SA analysis process. It may be noted that our model is not tied down to these specific representations or assumptions, and modifications and/or new approaches can be made according to the requirements. For a detailed explanation and analysis, please refer to [21].

3.1 Network Representation Component (NRC)[5]

As mentioned before, we use the graph-theoretic concepts of nodes and edges in order to model the effects of heterogeneity, hierarchy and dynamism on SA in typical NCO/NCW network. For the purposes of validating this model, we classify the nodes in our experimental setup into three types based on their roles. They are:

1) Sensor Nodes: contain sensors that monitor the environment for changes/events
2) Relay Nodes: are base stations that collect information from the sensor nodes belonging to its subnet
3) Fusion Nodes: receive event information from its subordinate relay nodes and assimilate the information and build the COP of the environment. Due to the hierarchical nature of the network, fusion nodes at the upper hierarchical levels have a broader view of the world.

In the network graph, delay in information flow due to queuing and transmission is modeled as part of the edge behavior. We use a Weibull distribution function $f(x;k,\lambda)$ [20] in order to represent the delay characteristics on each link. Weibull probability is mathematically more tractable for analysis and the shape of the curve can be easily controlled using just two parameters *k, λ*.

The nodes and connection in the NCO/NCW network is represented as a graph $G(V,E)$where $V = F_G \cup B_G \cup S_G$ is the vertex set representing the nodes in the graph and $E = F_E \cup B_E \cup S_E$ represent the edge set.
F_G, B_G, S_G are the set of fusion, relay and sensor nodes respectively.

$$F_E = \{(a,b) \in F_G \times F_G: a,b \in F_G, a = Authority(b)\},$$
$$B_E = \{(a,b) \in F_G \times B_G: a \in F_G, b \in B_G, a = Authority(b)\}$$
$$S_E = \{(a,b) \in B_G \times S_G: a \in B_G, b \in S_G, a = Authority(b)\}$$

Each element $v \in V$ in G has a set of labels that define its properties. Each label may have an associated weight when combined denote its qualitative/ quantitative measure. We now enumerate the labels and corresponding weights for the nodes and edges in the graph. We choose these particular labels to use in the experimental setup and validation. It may be noted that this choice of labels and weights is not rigid and can be changed according to our requirements.

Sensor Node:

a. *Sensing ability*: Type of events or properties of an event detected by the node
b. *Authority*: relay node that caters to this node
c. *Failure characteristics*: A probability distribution of the frequency with which the node moves out of its neighbors' transmission range. In this paper, we have defined failure characteristics for only sensor nodes. The

rationale being that sensor nodes work in the field and are also the most dynamic. Relay and fusion node are comparatively less mobile and better protected.

Relay Node:

a. *Authority*: fusion node that collect the information from this relay node
b. *Observation Zone*: is the geographic zone of operations associated with the sensor nodes working under the relay node

Fusion Node:

a. *Authority*: Other fusion nodes higher up in the hierarchy that this node sends the data to.
b. *Hierarchy level*: is the number of hops that this fusion node is away from the apex of the hierarchy.

Link:

a. *Delay characteristics*: We use Weibull distribution function $f(x;k,\lambda)$ in order to represent the delay characteristics on each link.

The NRC also models the information space using the concepts of events and event chains. A significant change in the environment detected by a sensor is called an event. We define event to be the fundamental units of the information layer with spatial and temporal characteristics. Typical scenarios consist of chains of events occurring one after another and culminating in a major event. We use Bayesian Knowledge Bases (BKBs)[7] to model the uncertainty and temporal dynamism of events and the emerging event chains. The framework for BKBs put forth by Santos and Santos[7] unifies the if-then-else style rules with probability theory, making it semantically sound, flexible and intuitive to understand. BKBs have an advantage over traditional Bayesian Networks because of their ability to provide representation to real world scenarios. BKBs represent objects, world states and the relationships between them using a directed graph. The graph consists of nodes which denote various random variable instantiations while the edges represent conditional dependencies/independencies between them. Let $\Re$ denote the real numbers, $\Re^+$ denote the non-negative reals, and ϕ denote the empty set.

Definition 1 (Def 1 from [7]): A correlation graph $\mathrm{G} = (\mathrm{I} \bigcup \mathrm{S}, \mathrm{E})$ is a directed graph such that $I \bigcap S = \phi$ and $E \subseteq \{I \times S\} \bigcup \{S \times I\}$. Furthermore, for all $a \in S, (a,b)$ and (a,b') are in E if and only if $b = b'$. $\{I \bigcup S\}$ are the nodes of G and E are the edges of G. A node in I is called an instantiation-node (I-node) and a node in S is called a support-node (S-node).

In our initial validation, we use the following set of labels in NRC to represent the information space. The labels are: a) *Active chains*: are event chains that are considered to be important and currently in progress. b) *Success Chains*: is the list of event chains that have been completed. c) *Failed chains/false alarms*: are chains that do not reach the leaf BKB node even after a long duration of time. d) *Event Record*: Each fusion node also has a list of events from the information passed on to it by other nodes. The time of occurrence and its positional coordinates are also stored. Fusion nodes also make prediction of the future events for the active chains it is monitoring and these prediction are also stored in the event record waiting for confirmation. These predictions are used by the node to make a decision on whether to continue monitoring this event chain and also if this information needs to be shared with other nodes.

3.2 Performance Measures Component (PMC)[5]

We formulate the SA model within NCO-PP by using the NRC component to represent the static network graph and the Performance Module Component to represent the dynamism. Prediction strategies for future events in the information space and changes in the network space are used for mapping the network state at different time snapshots. Based on these predictions of the future conditions of the network, each node can decide on how long to monitor particular events. This in turn affects the information sharing and filtering process in the network.

The various blocks (see Figure 1) in the implementation of PMC are the *Projection component*, *Network Effect Calculator* and the *Information Sharing component*. When a new event is received by a node, the *Projection component* will check its event record to determine if the event belongs to an existing event chain. The event record is updated regularly using the information from the NRC. The knowledge base contains some commonly occurring event chains. Using the information in the knowledge base, the prediction algorithm block calculates a set of future events. This set of events is relayed to the *Network Effect Calculator* to determine the network conditions in the regions where these future events are likely to happen. The *Network Effect Calculator* uses the information from the NRC to determine the network effect on the predicted future events, which is then relayed to the *Information sharing component*. The list of future events is also relayed to this component. Using the predicted network conditions and the predicted events, an optimal monitoring time is calculated. This is the time period for which the node will monitor the event chain. Depending on the occurrence of future events, this event chain may be downgraded or upgraded. An upgraded event chain will likely be sent to a higher level node and a downgraded event chain is sent to a lower level chain. The nodes at the highest levels have a broader perspective about the field, so there is a higher probability of "joining the dots" at this level. Hence there is a better chance for a more complete SA if the inference of the events is done at higher levels. In the *Optimal Monitoring Time Component*, we use a Cost-Reward methodology to model the information sharing in the network. There is a cost to a particular node paying attention to a particular event list. This cost increases monotonically with hierarchy level. Hence the cost of keeping an event chain in active list with higher level nodes is more than lower level nodes. This is to make sure that only the most important chains are considered by the higher level nodes and once the event chain priority decreases it is immediately pulled down. But in order to balance the effect of the cost, we have a reward system in the nodes for identifying a successful chain. This reward also increases monotonically with hierarchy. Each fusion nodes will try to maximize the rewards and minimize the cost based on the evidence they have about a particular event chain and in the process drive the information sharing and filtering paradigm in the network. By changing the values of the cost and reward, we can simulate various forms of information sharing and filtering including centralized processing and standalone/scattered processing.

The monitoring time allocation by a fusion node for a particular event chain can be formulated as a non-linear optimization problem. Let us consider a network with i hierarchy levels and the root node is said to be at level 1. An event chain represented as a BKB fragment is being processed by a node at level j. The optimal time for monitoring the particular event chain can be calculated from

$$\text{Maximize } \sum_{j=1}^{i} (fr_j) - \sum_{j=1}^{i} fc_j$$

Where, fr_j and fc_j are the expected reward and cost respectively, for node at level j

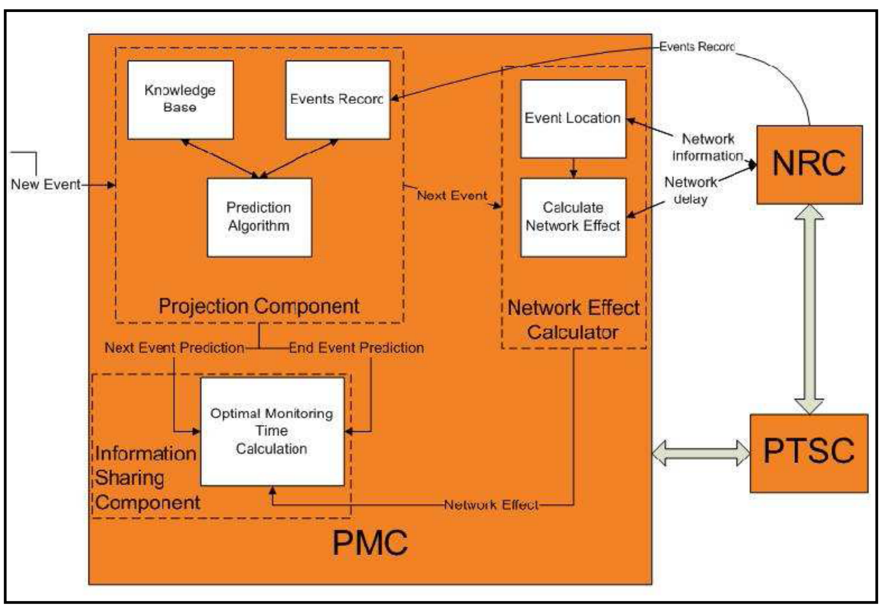


Figure 1 Implementation of PMC

3.3 Performance Tool Suite Component (PTSC)[5]

In PTSC, we define performance metrics that will measure the "completeness" of the SA generated and also seek to measure the efficiency of the information sharing and event prediction strategy adopted by the fusion nodes. These are measured using the General Awareness Factor (GAF) and Signal-To-Noise Ratio (SNR) measures respectively.

Let:

e_s: set of events belonging to successful chains

e_f: set of events flagged by fusion nodes from false alarms

T_s: set of events from successful event chains

General Awareness Factor	Signal to Noise ratio
$GAF = \frac{\lvert e_s \rvert}{\lvert T_s \rvert}$	$SNR = \frac{\lvert e_s \rvert}{\lvert e_s \rvert + \lvert e_f \rvert}$

3.4 Sub-component Interaction Component (SIC)[5]

Resource Allocation (RA) is an important aspect in any network and the resources considered may be in the form of bandwidth, computational resources or new nodes. RA is especially important in a dynamic network environment such as NCO/NCW where a certain performance is expected. The changing network conditions may adversely affect the information sharing in the NCO network leading to deterioration of SA and this can have very adverse repercussions on the mission at hand. The NCO-PP based SA model that we have described helps us in the real time analysis of the effects of network layer on the information layer. This analysis can be used to proactively allocate appropriate network resources so that the quality of the SA can be improved. We employ such a RA strategy in SIC that will recommend appropriate levels of resource allocation. In Figure 2, we describe the various blocks in our implementation of the SIC. When a new event is detected by a node, the SIC gets a set of possible future events from the PMC. In the *Event Visibility Calculation* block, the SIC gets the possible locations of these events and checks whether there are enough resources to observe the events. In the *Resource Allocator* block, the algorithm allocates sufficient resources based on the probability and importance of the future events. Then a recommendation for this resource allocation is made to the NRC. The two types of resources considered in our implementation are 1) Feeds and 2) Special Sensor nodes. Feeds are special information pathways attached to a node that can receive information from sensor nodes that are not in the same branch. These feeds allow lower level fusion nodes to get information that in normal conditions they are not entitled to. Special sensor nodes are highly mobile sensor nodes that can be quickly deployed in a geographical area that is not well covered. There are only a limited number of such sensors and their allocation is based on the importance of observing an event.

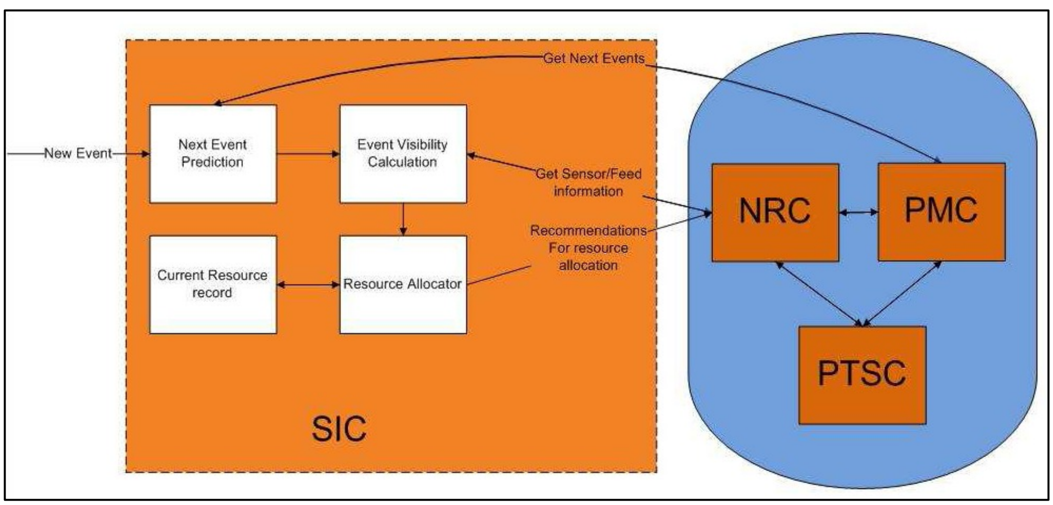


Figure 2 Sub-components of the SIC

4. EVALUATION

We run a set of experiments to evaluate our framework's ability to model various aspects of the SA process. For our first step, we experiment and evaluate the need for filtering information by comparing a hierarchical sensor system (A) with a system (B) which processes all information centrally at the apex node. Inherent simplicity of behavior, interaction and more complete awareness as a result of centrally available information are a few advantages system B has over system A. On the other hand, System A is scalable in terms of processing power and memory as the amount of incoming information grows; a situation which will render system B largely infeasible. In the next step, we explore if our model is able to test whether network dynamism has an apparent effect on SA in NCO/NCW systems; a largely unexplored intuition when we discuss such overarching frameworks. After establishing the effects of network dynamism on SA, we utilize the NCO-PP framework to explore whether adapting information sharing and resource allocation behavior by intuitively incorporating key network characteristics (network delay and node failure probability) can improve the level of SA in information systems. With these experiments we intend to test and verify the ability of this framework to model interactions between factors in network and information space. We also look to explore this framework's ability to provide insights into the performances of such systems while we try to analyze and predict theoretically intractable interactions.

4. 1 Experimental Setup

In order to simulate aforementioned experiments, we built a Discrete Event simulator in Python[19]. It was used to simulate a simple NCO/NCW network consisting of three levels of fusion nodes beginning at the apex level 1. Each fusion node in level 1 has two children, level 2 has 4 children. Each fusion node at level 3 receives information from 2 relay nodes. Each relay node has authority over 2 sensor nodes. The environment is divided into 9 distinct zones and each of the relay nodes is randomly placed in one of the zones. As far as simulating the information space is concerned, 90 types of events are considered. These events are scenario neutral in the sense that they do not denote any real life event. We form a number of event chains from the events making sure that the transition properties (e.g. Interval between two events) of these events correlate to real life situations. These event chains have around 8 I-nodes and 10 S-nodes. During the experimental run, 30 event chains are made to simultaneously evolve so as to realistically simulate the fast paced nature of the NCO/NCW environments. Each experimental run is for a period of 1000 time steps. The simulation is run in a LINUX environment on a machine with 2.2 GHz dual-core Centrino processor and 2GB RAM. Lindo API is used to do the non-linear optimization for Monitoring time calculations in the PMC.

4.2 Experiment 1

The aim of the first experiment is to contrast two approaches in information filtering: Hierarchical (Static Approach) and Centralized (Primitive Approach). Though it is a well established fact that hierarchical filtering is better (as evidenced by its wide spread adoption in NCO/NCW), we experimentally prove it as a way to validate our idea of using NCO-PP to build a model for SA. We now describe these two approaches in detail: (a) **Primitive Approach**: Information is centrally processed in the root node only. In the pseudo code given in Table 1, a) *Predictions(k)* refers to the predicted future events at fusion node *k*, b) *Level(k)* refers to the tier of hierarchy to which the fusion node *k* belongs and c) *Level(apex node)* is 1. (b) **Static Approach**: There is progressive information filtering at each level. In the pseudo code given in Table 1, a) *Records(k)* refers to the event record register at fusion node *k* and b) *EndConfidence(l,k)* refers to the probability of instantiating an end event if the scenario *l* progresses, according to the understanding of node *k*. We term the hierarchical approach as "static" since dynamic network information is not used.

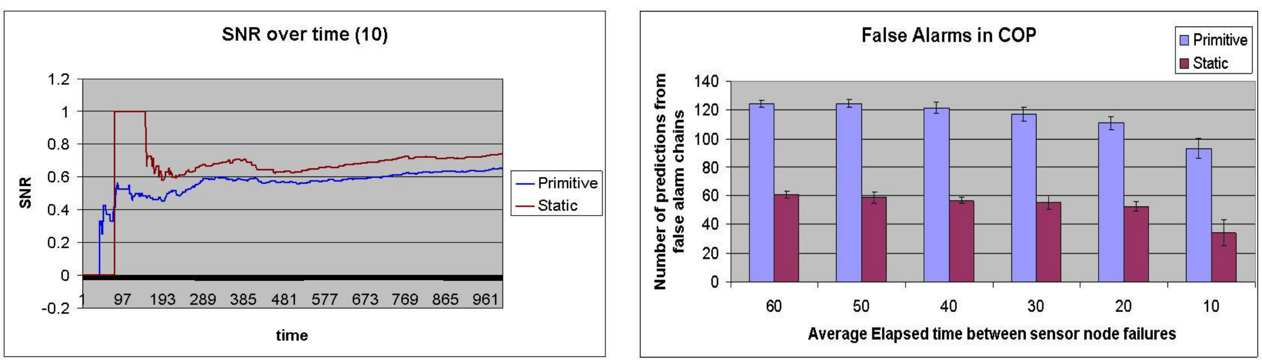
Hypothesis: We perform experimental runs to test the following hypothesis: *Information filtering at different levels in the hierarchy improves the quality of information in the general awareness picture (GAP).*

Results

In the experimental runs, we measure the quality of the SA in terms of Signal-To-Noise Ratio (SNR) at every time step. The run is repeated for different values of the network dynamism. Additionally, we count the number of false alarms among the events monitored by the network nodes. From the analysis of the results, we see that the quality of SA is better when hierarchical filtering strategy is adopted over centralized processing of events with no filtering. For lack of space, we present only a sample of the experimental results. We present the SNR Vs time graphs in Figure 3(a). A bar chart comparing the number of false alarms between the primitive and static system are shown in Figure 3(b). From the experimental results, we see that there is consistent better quality of information (SNR) in the system adopting hierarchical information filtering under dynamic conditions. In the *Primitive* System, apex operator will be overwhelmed by *false alarms.* This can be observed from the bar graph (Figure 3(b)) where we see that the number of false alarms (thought to be important) in Primitive approach is roughly twice the size of the Static approach. Hierarchical filtering retains significantly less percentage of false alarms, allowing more effective focus on critical situations.

Procedure for Primitive System	**Procedure for Static System**
for all event *i* do **for all** sensor *j* such that *j* records *i* do *j* routes *i* to the apex node *k* **end for** *k* adds *i* to update *Records(k)* *k* updates future event predictions *k* updates the corresponding scenario as (in)active **end for** At the apex fusion node *k* **for all** Active scenario $l \in$ *Records(k)* do if *EndConfidence*(l, k) $\geq$ 20% then Flag all knowledge and recorded events for the scenario *l* Reflect the flagged information in GAP **end if** **end for**	**for all** event *i* do **for all** sensor *j* which records *i* do *j* routes *i* to a fusion node *k* **end for** **for all** fusion node *k* such that *k* receives *i* do *k* adds *i* to update *Records*(*k*) *k* updates future event predictions *k* updates the corresponding scenario as (in)active **end for** **end for** At the each fusion node k: **for all** prediction *m* $\in$ *Predictions*(*k*) do Share prediction *m* up/down the hierarchy following the schedule obtained by Optimal Monitoring Time calculations **end for** **for all** Active scenario $l \in$ *Records*(*k*) do **if** *EndConfidence*(*l, k*) $\geq$20% $\times$*Level*(*k*) then Flag all knowledge and recorded events for the scenario *l* Reflect the flagged information in GAP **end if** **end for**

Table 1 Pseudo code for the information filtering in Primitive and Static Approach



(a)SNR Vs Time with Avg. Duration between failures = 10 (b) Ratio of false alarms

Figure 3 Results for various Dynamic Conditions in the Network in Experiment 1

4.3 Experiment 2

After validating the effect of information filtering on SA, we utilize our framework to understand the effect of incorporating the critical network characteristics into our model. We also try to determine whether incorporating the real time network information leads to substantial improvements in SA. In this experiment, we test the intuition "*Intuitively incorporating network delay characteristics in the information sharing/filtering process may improve the GAF factor*" and it should be significant under increased network dynamism.

Approaches

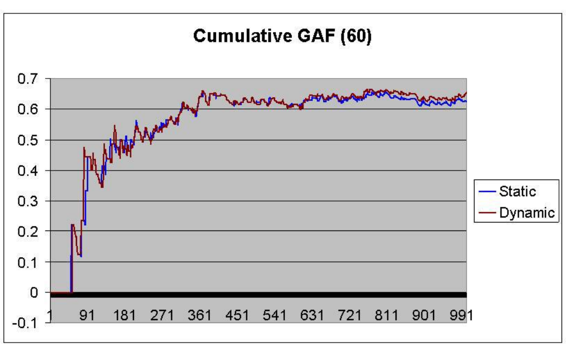
Here we compare the Static approach used in Experiment 1 with a Dynamic approach. The Dynamic approach is similar to the Static approach but with the additional capability to use network delay characteristics during information sharing. It uses real time state of the network in order to determine the events to monitor and the monitoring period. For details about the operation of these two approaches, please refer to the pseudo code in Table 2 where, a) *SendingDown(m, t, k)* checks if node k needs to send down/degrade the prediction/event m at time t according to the schedule obtained from calculation in the Optimal Monitoring Time calculation, b) *PathExists(k,m)* refers to all possible logical paths through which information about occurrence of event m will reach the fusion node k, c) *Delay(p)* refers to the current network delay on the logical network path p and d) *DelaySending(m, k,Mindelay)* is the routine which accommodates minimum delay information to defer degradation of event prediction.

In Static Approach	**In Dynamic Approach**
for all fusion node *k* and time step *t* do **for all** prediction *m* ∈ *Predictions(k)* do Share prediction *m* up/down the hierarchy following the schedule obtained from Optimal Monitoring Time Calculations **end for** **end for**	**for all** fusion node *k* and time step *t* do **for all** prediction *m* ∈ *Predictions(k)* do Share prediction *m* up the hierarchy following the schedule obtained from Optimal Monitoring Time Calculations **if** *SendingDown(m, t, k)* then Mindelay ← ∞ **for all** path *p* ∈ *PathExists(k,m)* do MinDelay ← Min(MinDelay,*Delay(p)*) *DelaySending(m, k,MinDelay)* **end for** **end if** **end for** **end for**

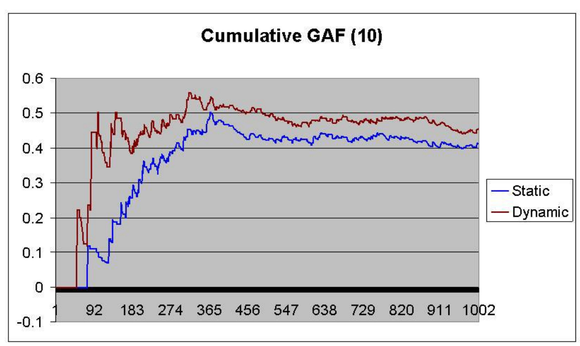
Table 2 Pseudo Code for the Static and Dynamic Approaches in Experiment 2

Results

In this experiment, we record the GAF at each time step of the experiment. This experiment is repeated for different values of the network dynamism. For lack of space, we provide the graphs for only two node failure rates in Figure 4. Table 3 gives the lower range of the GAF experimental results of the Dynamic approach and the upper range of the Static approach. We expect that the quality of the SA for the Dynamic Approach will be better than Static and this contrast will be magnified when the network dynamism is high. We make the following main observations from the experimental results. In Figure 4, (a) displays the GAF for highly dynamic network and (b) is for lightly dynamic network. By comparing these two graphs, we see that the quality of the SA in the Dynamic approach is better than the static approach and this divergence is greater when the network dynamism is high. Hence we observe a decisive advantage of using network delay characteristics while sharing information in a hierarchical network. We included Table 3 to demonstrate how the difference in the lower GAF range of the Dynamic approach and the upper GAF range of the Static approach, increases with higher dynamic conditions. It also indicates that the dynamic approach has increased resistance as compared to the static approach against the deteriorating effect of network dynamism. Our experimental results help in recognizing the positive impact of incorporating network delay in information sharing on the completeness of SA in highly unstable environments.



(a)Avg. Duration between failures = 60



(b)Avg. Duration between failures = 10

Figure 4 Cumulative General Awareness Factor Plots for different dynamic conditions in Experiment 2

We make the following main observations from the experimental results. In Figure 4, (a) displays the GAF for lightly dynamic network and (b) is for highly dynamic network. By comparing these two graphs, we see that the quality of the SA in the Dynamic approach is better than the static approach and this divergence is greater when the network dynamism is high. Hence we observe a decisive advantage of using network delay characteristics while sharing information in a hierarchical network. We included Table 3 to demonstrate how the difference in the lower GAF range of the Dynamic approach and the upper GAF range of the Static approach, increases with higher dynamic conditions. It also indicates that the dynamic approach has better resistance against the deteriorating effect of network dynamism than the static approach. Our experimental results helps in recognizing the positive impact that incorporation of network delay in information sharing, has on the completeness of SA in highly unstable environments.

	60	50	40	30	20	10
Static U-range	0.737	0.712	0.714	0.687	0.624	0.472
Dynamic L-range	0.737	0.731	0.716	0.690	0.618	0.522
Dynamic L - Static U	0	0.019	0.002	0.003	-0.006	0.05

Table 3 Comparison of Lower(L) and Upper(U) GAF Ranges for the Two Approaches in Experiment 2

4.4 Experiment 3

As the next step to Experiment 2, where we demonstrated the significance of incorporating network delay characteristics in effectively modeling situation awareness, we now focus on using the dynamic network information for proactive resource allocation decisions.

Hypothesis: This experiment allows us to explore if modeling the dynamic information and network space can lead to effective and better utilization of limited resources. This is in contrast to a more naïve approach of resource allocation guided solely by the information state requirements. Hence the hypothesis that we seek to prove is: *Taking sensor node failure characteristics into account while making decisions for dynamic resource allocation will improve the completeness of resulting situation awareness or GAF.*

Our Approaches: We compare *Proactive-Base*, resource allocation guided by requirements of information space only, with *Proactive-limited* where resources are allocated taking into consideration both network dynamism and information space requirements. Both of these approaches are extended from the dynamic approach described in Experiment 2 and allow us to increase the complexity of our framework in a controlled manner. This experiment further tests the ability of NCO-PP framework to represent increasing complexity and bring together advances in different network and information domains under a common lens.

In the following section we describe the salient features of both the approaches compared in this experiment.

Proactive-Base:

1) This approach represents hierarchical distributed information gathering systems following information filtering paradigm and leveraging information about network characteristics for sharing information.

2) The approach does not take into account network state/characteristics while allocating resources.

3) This approach does not have upper-bound on the amount of deployable resources.

4) Overall probability that a particular prediction may not be observed goes to zero if at least one sensor node can monitor the event and the information can be delivered to the concerned fusion node.

Proactive-Limited:

1) This approach represents hierarchical distributed information gathering systems following the hierarchical information filtering paradigm and leverages network characteristics while sharing information.

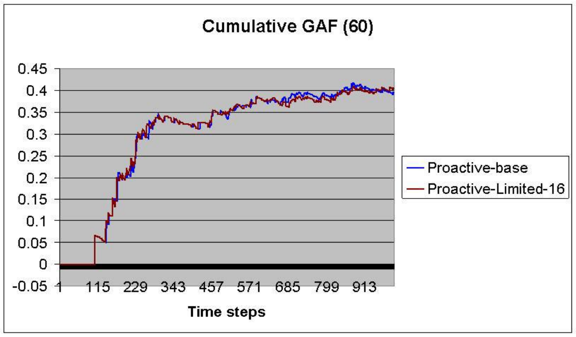
2) This approach takes network characteristics into consideration while allocating resources in real time.

3) This approach has specific upper bounds on the number of resources it could deploy.

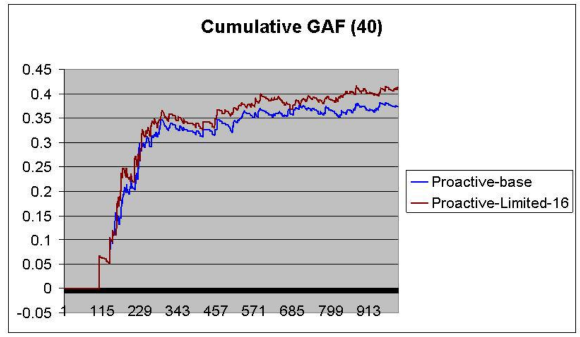
4) For a fusion node predicting an event, the probability of not being able to observe the event decreases by the factor of the sensor node failure probability for each sensor that can detect instantiation of the prediction and evidence relayed to the fusion node.

Results

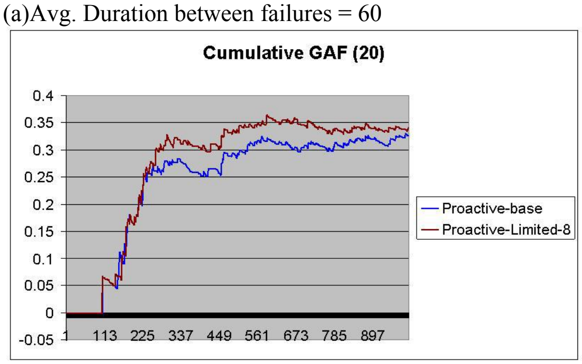
As before, we record the GAF for each time step. We not only run the experiment under various dynamism rates but also with different amounts of available resource for the *proactive-limited* approach. These are essentially Special sensors (described in Section 3.4) available for temporary deployment. We run experiments on *proactive-limited* keeping the upper bounds on the special sensors to be 6, 8, 24 and 32. From Figure 5, we can decisively say that *proactive-limited* approach provides better and more complete GAP as compared to *proactive-base*. The results displayed show the minimum resources required by the *proactive-limited* to perform better than the *proactive-base* approach. It may be also noted at higher rates of dynamism, *proactive-limited* require more sensors to beat *proactive-base*. As the *proactive-limited* approach is a heuristics based approach, it does not always guarantee the optimum solution. As part of the future work, we aim to develop more sophisticated resource allocation strategies. However we were able to demonstrate with this experiment that a simple and intuitive heuristics based approach can provide consistently better results and maximum GAF when network characteristics are considered during resource allocation.



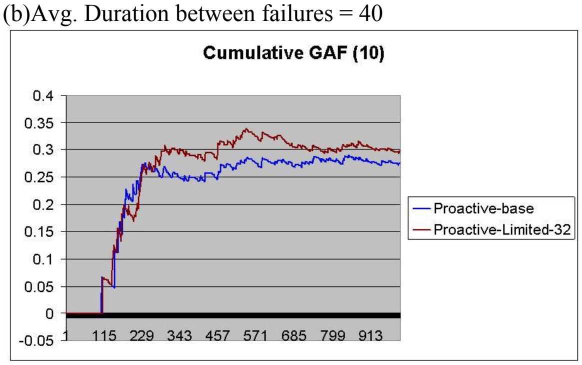
(a)Avg. Duration between failures = 60



(b)Avg. Duration between failures = 40



(c)Avg. Duration between failures = 20



(d)Avg. Duration between failures = 10

Figure 5 Cumulative GAF for various network dynamism rates in Experiment 3

5. CONCLUSION

In this paper, we formulated a performance model within the framework of NCO-PP. By conducting simulations studies on a 3-tier hierarchical sensor network, we successfully demonstrated the necessity of representing the decision making and network aspects of SA and their interactions for a realistic SA model. As an initial step, we used our model to validate the fact that information filtering is necessary for scalable performance of SA. Specifically, we showed that there is a 47% reduction in the number of false alarm events with hierarchical information filtering over centralized processing. We also demonstrated the information sharing policies which are vital for effective SA should take the deteriorating effect of highly dynamic network conditions into account. In fact by doing so, we see that there is a 10% improvement in SA performance. Our model can also be used to guide the users in deploying resources efficiently. The resource allocation strategies that we deployed in our experimental studies led to a 5% improvement in SA performance over baselines that did not take network dynamism into account. In short, we have successfully demonstrated the superiority of our modeling paradigm over traditional SA models that make simplifying assumptions of the network conditions.

ACKNOWLEDGEMENTS

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