

# MASM: A market architecture for sensor management in distributed sensor networks

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## ABSTRACT

Rapid developments in sensor technology and its applications have energized research efforts towards devising a firm theoretical foundation for sensor management. Ubiquitous sensing, wide bandwidth communications and distributed processing provide both opportunities and challenges for sensor and process control and optimization. Traditional optimization techniques do not have the ability to simultaneously consider the wildly non-commensurate measures involved in sensor management in a single optimization routine. Market-oriented programming provides a valuable and principled paradigm to designing systems to solve this dynamic and distributed resource allocation problem. We have modeled the sensor management scenario as a competitive market, wherein the sensor manager holds a combinatorial auction to sell the various items produced by the sensors and the communication channels. However, standard auction mechanisms have been found not to be directly applicable to the sensor management domain. For this purpose, we have developed a specialized market architecture MASM (Market architecture for Sensor Management). In MASM, the mission manager is responsible for deciding task allocations to the consumers and their corresponding budgets and the sensor manager is responsible for resource allocation to the various consumers. In addition to having a modified combinatorial winner determination algorithm, MASM has specialized sensor network modules that address commensurability issues between consumers and producers in the sensor network domain. A preliminary multi-sensor, multi-target simulation environment has been implemented to test the performance of the proposed system. MASM outperformed the information theoretic sensor manager in meeting the mission objectives in the simulation experiments.

**Keywords:** Sensor Management, Market-oriented programming, Combinatorial Auctions, Genetic algorithms.

## 1. INTRODUCTION

Recent strides in sensor technology have led to a proliferation of different kinds of sensors and sensor applications both in civilian and military domains [1]. Multi sensor systems rely on data fusion techniques to combine data from multiple sensors and related information to achieve more specific inferences than could be achieved by using a single, independent sensor [2]. A key aspect of data fusion is sensor management which may be defined as “a process which seeks to manage or coordinate the use of sensing resources in a manner that improves the process of data fusion and ultimately that of perception, synergistically” [3]. Modern sensor management techniques should be able to operate sensors synergistically to take full advantage of each sensor’s strengths while not underutilizing any other sensors. Sensor management system’s responsibilities include automation of sensor allocation, moding, pointing and emission control, prioritization and scheduling of service requests, coordinating fusion requests with data collected from different sensor and sensor modules, supporting reconfiguration and degradation due to loss of sensors or sensor modes and communication of desired actions to the individual sensors. Sensor management algorithms map into level 4 data fusion of the JDL model which is concerned with the optimization of sensor or information sources utilization and algorithms to achieve the most useful set of information [2].

Rapid developments in sensor technology and its applications have energized research efforts towards devising a firm theoretical foundation for sensor management. Ubiquitous sensing, wide bandwidth communications and distributed processing provide both opportunities and challenges for sensor and process control and optimization. Limited sensor processing and battery capacities, the underlying heterogeneity of the various sensors add more dimensions to this complicated problem. Furthermore, distributed sensor networks can be utilized by multiple users, operating in a semi-cooperative environment with little or no communication between them.

Finally, in these systems, humans can take the role of sensors, data collectors, or mission managers dynamically setting the priority of mission goals in the sensor network. Traditional optimization techniques do not have ability to simultaneously consider these wildly non-commensurate measures in a single optimization routine. We believe that market-oriented programming [4], provides a valuable and principled paradigm to designing systems to solve this dynamic and distributed resource allocation problem.

Market-oriented programming refers to the design and implementation of distributed resource allocation problems based on some pricing system. Market-based algorithms have been used for resource allocation in distributed allocations in a wide ranging of scenarios including bandwidth allocation [5], network information services [6], digital libraries [7], distributed operating systems [8] and electric load distribution [9] etc. Market mechanisms have also been applied to scheduling with promising results [10]. This approach uses the fundamentals of economic theory for designing and implementing resource allocation problems. The basic idea behind these algorithms is that price based systems facilitate efficient resource allocation in computational systems, just as they do in human societies. Resource-seeking entities are modeled as independent agents, with autonomy to decide about how to use their respective resources. These agents interact via a market that uses a pricing system to arrive at a common scale of value across the various resources. The common-value scale is then by used the individual agents for making trade-off decisions about acquiring or selling goods. Market-oriented programming essentially involves designing the mechanism in which agents interact to determine prices and exchange goods.

Market-oriented approaches usually involve auction mechanism, where agents send bids to an auctioneer for various commodities and the auctioneer determines the resource allocations. Auctions can be defined as “a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants” [11]. In the standard auction mechanisms, individual goods are auctioned independently of each other. In a scenario where agent utilities for various goods show strong complementarities as is the case with sensor networks, these mechanisms can lead to inefficient allocations [11]. For example, consider a sensor simulation scenario where a distributed sensor network tracks a moving target. To maintain the target track, not only measurements should be scheduled over the various sensors but also, bandwidth for measurement communication to the fusion system should be reserved. Scheduling measurements may not be of any use to the consumers unless bandwidth to communicate the measurements is also available. Combinatorial auctions where agents bid on a combination of items allow the bidders to express this kind of synergistic relationship between goods [12]. But, winner determination in combinatorial auctions is NP-complete and there has been a lack of algorithms that can meet the strict real-time constraints of sensor management. Recent years have seen great strides into research in this problem, resulting in algorithms that are polynomial in the number of bids [12, 13], spawning the present research work.

Based on the principles of Market-oriented programming, we have developed MASM (Market Architecture for Sensor Management). Section 2 presents MASM architecture and a description of the various MASM modules. Section 3 presents the details of a preliminary simulation environment that has been implemented to test the performance of MASM. Section 4 presents the results of the simulation study conducted. The final section discusses the directions for future research.

## 2. MASM DESCRIPTION

The market design that we propose to use in sensor management domain is given in figure 1. The mission manager allocates the various task responsibilities and their corresponding budgets to the consumer agents in the market. The sensor manager holds an auction where the goods owned by the individual sensors like measurement schedules, battery power and processing capacity and bandwidth of the transmission channels are auctioned off to the consumers. Consumers bid for various goods required for accomplishing the tasks allotted to them, using the budget provided by the Mission Manager. This design cannot be directly adapted to implement a market mechanism for sensor management. Additional difficulties exist due to a variety of reasons, explained below. First, as shown in Figure 1, usually consumers in a sensor network are interested in commodities like target tracks, environmental searches etc. On the other hand, the individual sellers in the sensor management domain can produce only measurement data or communication bandwidth. Thus, it is clear that some method for bundling goods produced by various sellers is essential to create commodities that consumers are interested in and can bid for. Also, in a traditional auction mechanism, a single item can be allocated only to a single consumer. This is not the case with the

sensor network domain. For example, if consumer A is interested in scanning an area at rate  $r_1$  and consumer B is interested in scanning the same area at rate  $r_2 > r_1$ , then a single commodity i.e. a scan at rate  $r_2$  can be communicated to both agents and will satisfy both of them. Thus, there can be a one to many mapping between the commodities in the market and allocations to the agents. In addition to these difficulties, sensor management has very strict real time constraints. This implies that the market mechanism should be able to produce feasible if not optimum allocations in very little time.

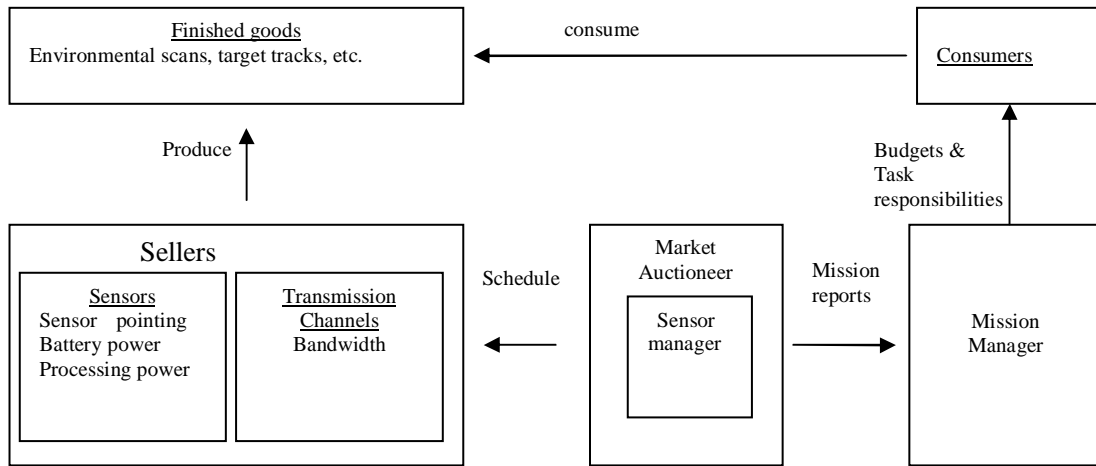


Figure 1. Market Design for Sensor Management.

For these reasons, traditional auction mechanisms are not directly applicable to sensor management scenario. A specialized architecture, Market Architecture for Sensor Management (MASM) has been developed for this purpose (figure 2). MASM closely resembles the architecture proposed by Dentol et al [22]. MASM's mission manager (MM) is responsible for mission level decisions like the priority of various tasks to mission goals and their respective budgets. MM is also responsible for task allocation to the various agents when multiple task accomplishing agents are involved. MM receives periodic updates about the mission status from the sensor manager and uses this information to allocate budgets and tasks to the various consumers.

MASM'S sensor manager is responsible for allocating sensors and bandwidth to various tasks, sensor scheduling and fault diagnosis. Individual sensors are responsible for making measurements of the environments, as per the schedule given the sensor manager and communicating these measurements to the fusion center, which is designated by the SM and is responsible for data fusion, required for the concerned task. MASM models the sensor management function as a competitive market where the different actors responsible for their tasks send bids for various tasks. Sensors that provide sensing capabilities and transmission channels that provide bandwidth capacity are modeled as sellers in the market. Sensors sell the sensor schedule, battery and processing power and the transmission channels sell raw bandwidth in the market. However, consumers of the sensor network are interested in higher end products like target tracks, environmental searches, target identification etc. Therefore, a standard combinatorial auction mechanism where consumers directly bid for sellers' goods cannot be used. To address this issue, SM has two specialized modules, the bid formulator and the service chart that bundle the raw products available in the market into products that consumers are interested in. SM accepts consumer bids in the form of  $\langle \mathbf{t}, \mathbf{p} \rangle$  where  $\mathbf{t}$  is a task description including the minimum task quality that is acceptable to the consumer and  $\mathbf{p}$  is the price the consumer is willing to pay. The SM module, bid formulator, translates these bids into a form that can be directly used in a standard combinatorial auction algorithm. For this purpose, bid formulator uses the service chart that contains information about the services provided by the various sensors and transmission channels. The bid formulator enumerates the different possible allocations for each task in the consumer bids and then uses the price quotes in the consumer bids to evaluate the price quotes for each allocation. Once the bids are formulated, the combinatorial auctioneer module of the sensor manager uses anytime combinatorial search algorithm like CABOB [13] to find an optimal allocation. We are currently working on modifying CABOB to address the issue of the

possibility of one to many mappings between resources and consumers in a sensor management scenario. However, since both the algorithms are exponential in the number of items in the worst case, we are also developing heuristic search procedures like genetic algorithms for winner determination in combinatorial auctions. As part of future work, we intend to conduct a comparative study of the performance of various winner determination algorithms in terms of their real time performance.

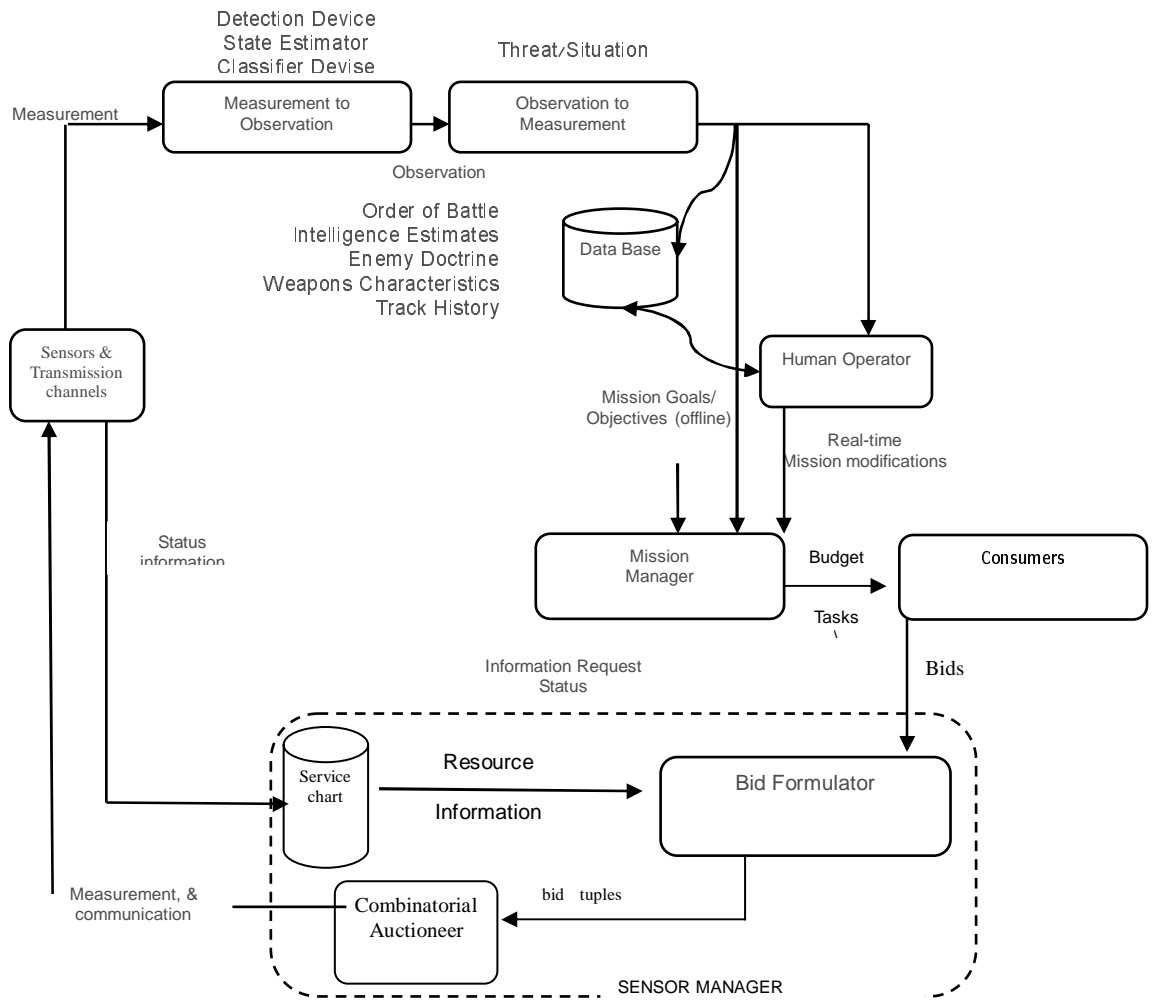


Figure 2. MASM architecture.

### 3. SIMULATION ENVIRONMENT

The simulation environment consisting of a two dimensional search area involving multiple targets and multiple sensors has been developed for testing MASM and comparing its performance with other sensor management approaches. The search area is organized as rectangular cells within which targets are randomly distributed. Targets are constrained to move only within a cell with a constant velocity corrupted with a white noise. Each sensor's capabilities and performance is modeled using a Kalman filter observation matrix (one for each sensor) and noise variance of their measurements. The simulation environment has consumer agents which are assigned the responsibility of searching for and destroying the targets. This preliminary simulation environment does not model bandwidth, battery power and processing power constraints. The various MASM components that have been used in

the simulation are described below.

### 3.1. Target modeling

Targets are randomly distributed throughout the search area. Targets are constrained to move only within a cell with a constant velocity corrupted with a white noise. The target motion is simulated by the equation

$$x_k(t+1) = x_k(t) + w_k$$

where  $x_k(t+1)$  and  $x_k(t)$  are positions of the target at time  $t$  and  $t+1$  respectively and  $w_k$  is the white noise with known constant covariance  $Q$ .

### 3.2. Sensor Modeling

Sensors can be made to point in four different directions and have two modes of operation: high resolution and low resolution scan. In the low resolution scan mode, sensors can look at a larger area but with lower resolution and vice versa. Sensors are distributed throughout the simulation environment such that all the environment grids fall under the purview of at least one sensor. Each sensor's capabilities and performance are modeled through a Kalman filter observation matrix (one for each sensor) and noise variance of their measurements. The measurement matrix for  $i$ -th sensor is

$$z_i(k) = x_i(k) + v_i(k)$$

where  $x_i(k)$  is the state vector, and  $v_i(k)$  is zero mean white noise with known variance  $R_i$ .

### 3.3. Consumer Agents

The environment consists of a set of consumer agents, each of whom is assigned an area of responsibility within which they are responsible to search and destroy targets. Consumers have an area of influence, wherein they can directly pursue and destroy targets. After destroying targets within an influence area, the consumers move to the next influence, as long as there are unexplored areas within their area of responsibility. Consumer agents bid for various sensor services to the sensor manager and use the services assigned to update the target position information. Targets are destroyed if consumers attack a position that falls within a prescribed distance, *attack\_length*, of the actual target position. Consumers attack a target if they can ascertain its position within the *attack\_length* range, with a probability greater than a threshold value, *attack\_probability*. MASM allows the consumer agents to determine the bid value for each task. In this simulation, consumer agents use the goal lattice values [14] to divide their budget into detection and track budgets. The track budget is divided equally among all the existing target tracks that the consumer is interested in and the detection budget is divided equally among all the unexplored cells in the consumer's influence area. Consumer bids are of the form  $\langle t, p \rangle$  where  $t$  is the task description including the specification of the minimum quality to which a task has to be performed and bid price is the budget of the corresponding task. For example, a bid for target tracking specifies the maximum uncertainty allowed in the target position (as required by the *attack\_length* parameter) and a price that the consumer is willing to pay for the task. The target is attacked if its position can be ascertained within the *attack\_length* range, with a probability greater than a threshold value, *attack\_probability*.

### 3.4. Sensor Manager

The sensor manager has two modules, the combinatorial auctioneer and a bid formulator. The bid formulator is used to create bid tuples from the consumer bids in a form that can be directly used by the combinatorial auctioneer. For example, a consumer bid for a target track is in the form of  $\langle t, p_t \rangle$  where  $t$  is of the form "*track object A to a maximum error covariance k*" and  $p_t$  is the price the consumer is willing to pay for the task. The bid formulator converts this consumer bid into the form " $\langle \text{low power scan of sensor 1, } p_1 \rangle$  or  $\langle \text{low power scan of sensor 2, } p_2 \rangle$  or  $\langle \text{low power scan of 1, low power scan of sensor 2, } p_3 \rangle$ ". To convert to this form, the bid formulator uses the service chart that contains information about the distribution of the sensors in the environment and their operating parameters. For calculation of the price quotes for the various bids, the bid formulator uses the concept of sensor services. A sensor service  $S$  is defined as a set of sensor measurements on any particular cell. For each cell in the environment, the bid formulator computes the various possible sensor services and their corresponding utilities based on the consumer bids. The utilities for the sensor service are calculated in the following way. Let the consumer bid for a particular task be  $p_t$ . For a given sensor service  $S$ , let  $n$  be the no of continuous such services required to perform the task to the required quality. Hence, the sensor manager requires  $n$  consecutive allocations of service  $S$ , before the task can be considered accomplished. The utility for the

service is evaluated as  $p_t/n$ . For example, if a particular target requires three consecutive low resolution scans before the error covariance of its state vector is reduced below the threshold value, then the utility of a consumer agent for a sensor service consisting of a single low resolution scan is  $p_t/3$ . Finally, the combinatorial auctioneer uses a genetic algorithm (GA) to find the optimum sensor allocation, after the bids are formulated in the required format.

### 3.5. Mission Manager

Mission manager is responsible for allocating budget to the various tasks and the task responsibilities to the various consumers, based on the mission status reports generated by the sensor manager. In this simple scenario, the mission report send by SM consists only of the target probability distributions. The mission manager divides the total budget among the various consumers in the ratio of the expected number of targets under each consumer's purview.

### 3.6. Information-Theoretic Sensor Management

To compare performance of MASM, we have implemented an information theoretic sensor manager. Information theoretic sensor management has gained prominence in the research literature in the last few years. Hint K.J and McVey E.S. [7] have suggested that information theoretic measures have the potential to serve as a theoretical foundation for sensor management. McIntyre et al [1] have used information gain (the entropy change in environment for a given sensor allocation) as the predicate for their hierarchical sensor management architecture. The information theoretic sensor manager schedules sensors to minimize the entropy of the environment. The amount of information gained can be measured by the change in entropy prior to and proceeding a sensor measurement. Entropy,  $H(x)$  of a probability density (mass) function is defined as

$$H(x) = \sum p(x_i) \log p(x_i) \quad \text{for the discrete case}$$

$$= \int p(x) \log p(x) dx \quad \text{for the continuous case}$$

where  $p(x)$  is the probability density (mass) function for the continuous (discrete) distribution. Assuming a normal distribution of target location, the information gain i.e., the difference between the a priori and a posteriori entropies is

$$I = \log_2(\sigma_a / \sigma_b)$$

where  $\sigma_a$  is the error covariance of the distribution and  $\sigma_b$  is the error covariance before the measurement. The error covariance matrix  $P$ , maintained by the Kalman filter process can be calculated offline and can be used in the calculation of the information gain, using the relation

$$\sigma = \sqrt{|P|}$$

where  $|P|$  is the norm of matrix  $P$ .

The approach to calculating information gain for detection is similar to that of tracking, except that the calculated information gain is multiplied by a constant  $\gamma$ , the prior probability that a target is indeed present in a cell.

## 4. RESULTS

The game parameters used in the simulation experiments are given in table 1. In the low resolution scan, sensor can scan an area of four cells, whereas in a high resolution scan, it can scan only one cell. The measurement error covariance for low resolution scan is chosen to be 50% more than the measurement error covariance for high resolution scan. The parameters used by the GA routine in the sensor manager are given in table 2. The parameter `attack_probability` was set as 95%. When the parameter `attack_length` is set very low, neither of the sensor management approaches performed well because the error covariance of target tracks required for the consumers to successfully destroy a target is below the steady state error covariance of the sensors' Kalman filter. On the other hand, if the `attack_length` is set high, target destruction became very easy and there was no difference between information-theoretic sensor management and MASM. Therefore, `attack_length` was set at a median value of  $9 \times 10^{-3}$ . The GA parameters used by the combinatorial auctioneer are shown in table 2.

No of Grids	64
No of targets	12
No of sensors	5
Measurement error covariance for High Resolution scan	$1 \cdot 10^{-3}$
Measurement error Covariance for low resolution scan	$1.5 \cdot 10^{-3}$
Process error covariance	$10^{-3}$
attack_length	$1.8 \cdot 10^{-3}$
attack_probability	0.95

Table 1. Game Parameters

No of Generations	50
Population Size	50
Mutation Probability	0.01
CrossOver Probability	0.9
Tour Size	4

Table 2. GA parameters

Hundred simulation games were run to compare the performance of MASM and information theoretic sensor manager. Consumer agents using the MASM architecture were able to completely destroy the targets in all the games. The average number of iterations that was required by MASM to destroy all the targets and complete the game was 12.4. On the other hand, the information theoretic sensor manager, on an average, could destroy only 7.2 targets. Figure 3 shows the change in the number of undetected targets with iterations for both sensor managers in a typical game. Figure 4 shows the change in the number of targets existing in the field with iterations for both sensor managers. Figure 5 shows the average error covariance of the target tracks for MASM and the information-theoretic sensor manager for the same game. As can be seen, the average target track error covariance in information-theoretic sensor management reaches an asymptotic value after a few iterations and the information-theoretic sensor manager fails to reduce the entropy of the simulation field beyond a certain limit. It is clear that MASM is more successful in meeting the mission objectives and consumer constraints than the traditional information-theoretic sensor manager.

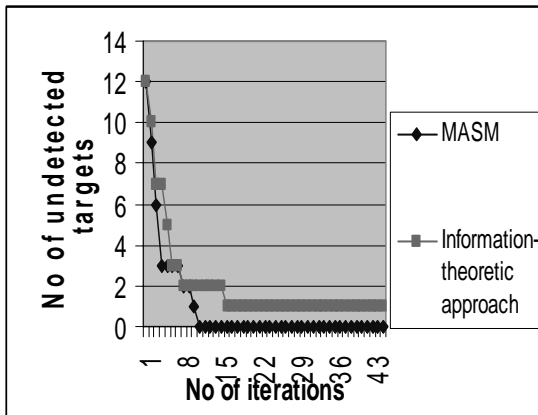


Figure 3. No of undetected targets in simulation environment

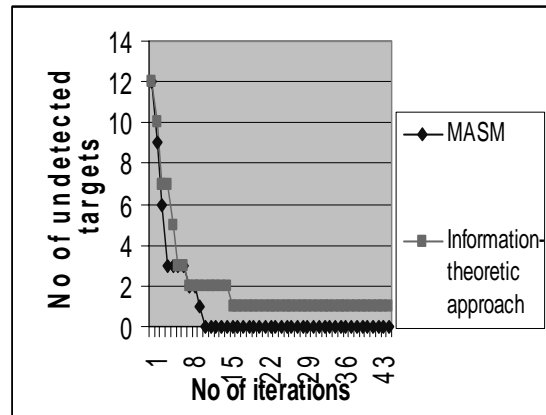


Figure 4. No of target existing in simulation environment

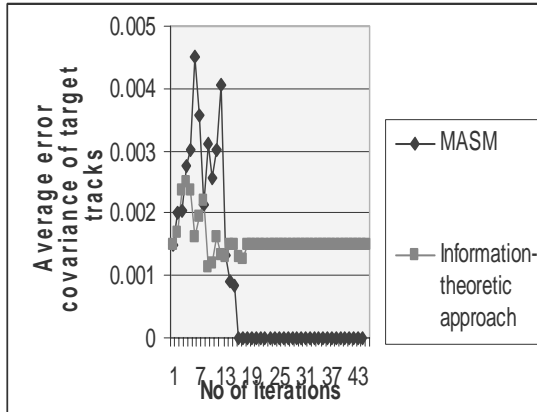


Figure 5. Average Error Covariance of target tracks

#### 4. CONCLUSIONS

A market architecture for sensor management based on a combinatorial auction mechanism has been proposed. Preliminary results obtained from a multi-sensor, multi-target simulation environment show promise. We are currently building a more realistic simulation test bed with heterogeneous sensors, bandwidth, battery power and processing power constraints to conduct comparative studies of the various sensor management approaches.

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