Improving the Science Return from Coastal Sensor Webs Using Autonomous Predictive Control and Resource Management

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Abstract

We describe the use of model predictive control as an integrated framework for optimal resource management in an ocean monitoring and predictive sensor network. The technique is used to adapt the operation of all the sensor and communication resources of the network to changing events in the area being monitored. The optimal control output determines the sampling rates of static sensors, paths of underwater unmanned vehicles, and wireless communication parameters. The system operates on data obtained from a variety of sources including static sensors, unmanned underwater vehicles, and sensors attached to passing cruise ships. Our sensor web adaptive control solution was found to improve the accuracy of event modeling and prediction by 50%. This novel solution is directly applicable to a variety of sensor webs and paves the way for coordinating multiple ground and space assets for faster, better detection, tracking and characterization of earth and extra-terrestrial environments.

1. Introduction

Coastal zones are dynamic regions, occurring at the interface of the terrestrial, oceanic and atmospheric domains and intersecting with large, growing human populations. Given this importance, there is a compelling need to detect, understand, and predict climate (e.g., sea level rise) and event-scale (e.g., coastal storm surges, spills) variability. In order to achieve this goal, networks of sensors have been deployed in many coastal regions to continuously measure ocean conditions and transmit the data to researchers. Such systems are called ocean sensor networks or webs.

Monitoring of the world's oceans is important for a variety of environmental and economic reasons. Ocean monitoring becomes particularly important near densely populated regions such as the New Jersey Atlantic Ocean shoreline. In these situations, a predictive model of the ocean can provide warnings of dangerous water conditions, identify conditions that will affect water quality, and to aid economic activity such as calculating passageways for ships entering a busy harbor. However, hydrodynamic model predictions will differ from real-world conditions due to reasons such as approximations in the model formulations, and the limited resolution of sensor measurements that form the input to these models. In such cases, it is beneficial to assimilate a limited set of real-world sensor measurements to the model in order to increase the prediction accuracy of the ocean monitoring system. However, obtaining sensor measurements from a sensor network consumes resources such as energy and communication bandwidth. In the case of embedded sensors, these resources are likely to be limited. Thus, in order to achieve this assimilation efficiently it is necessary to efficiently manage the resources of the entire sensor network in response to dynamic events.

In our technology efforts under Autonomous In-situ Control and Resource Management in Distributed Heterogeneous Sensor Webs: CARDS, we developed a technique to improve the science return from

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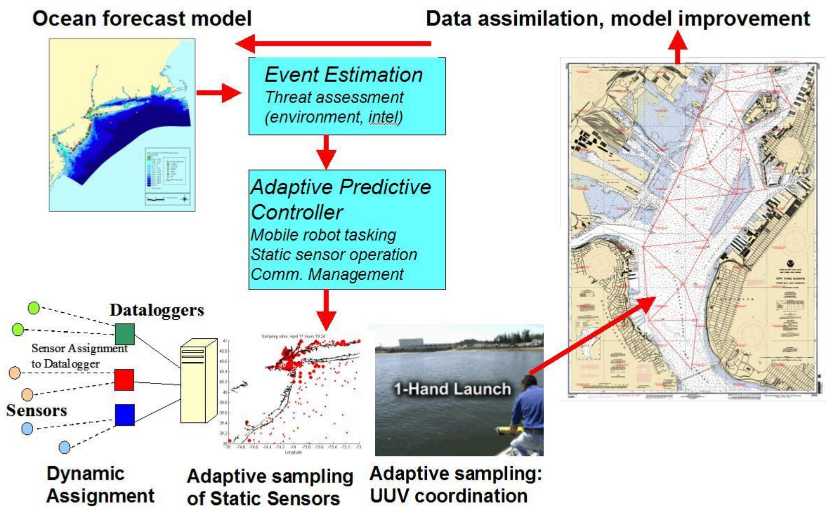

Figure 1: Adaptive control and resource management of sensor web parameters and operations in response to events.

deploying an ocean sensor web by adapting the system parameters that affect the utility of the sensor measurements (for instance, sampling rates of the sensors) and the rate of system resource utilization (for instance, energy expenditure rates of sensors and data routes in wireless transmission) such that these two competing factors are optimized in such a way that events in the environment are monitored for extended periods (Figure 1). Our ocean sensor web control and resource management approach uses the established mathematical framework of model predictive control. We illustrate how our approach can improve the prediction accuracy of a coastal environment monitoring network that operates in the New York Harbor and extends into the New York Bight [1].

1.1 Ocean Sensor Web Autonomy and Relevance to NASA ESTO

Ocean sensor webs provide the potential for an improved ability to effectively observe, understand, and predict variability and change in coastal marine ecosystems, contributing to improved scientific knowledge and decision-making and ultimately significant societal benefits, which is of primary interest to the NASA ESE and NASA ESTO. Towards fulfilling this need, the U.S. is developing the Integrated Ocean Observing System (IOOS), of which the NYHOPS is a key local/regional component. IOOS is the U.S. component of the Global Ocean Observing System (GOOS), to be a key part of the emerging Global Earth Observing System of Systems (GEOSS).

While the IOOS is driving the implementation of much needed *in-situ*, ground based observing networks, the current deployed systems typically consist of uncoordinated fixed, mobile observing assets that generally operate independently of one another.

CARDS will directly enable critical autonomous coordination capability for effective and accurate detection and prediction of the episodic, short-lived coastal events (e.g., storm surges, rip tides, spills/runoff) and characteristic of coastal regions, via resampling and retargeting of static and mobile (vessel) surface sensor assets.

In terms of immediate, short-term benefits and relevance, improved detection of the onset of episodic events within the NYHOPS domain and the improved sampling of such events through CARDS will directly improve the well-being and safety of the NY/NJ coastal community and maritime interests. Specifically, improved assessments and predictions of storm surges, rip currents, harbor current anomalies and pollutant/hazard fate and transport will benefit local (county/state) and federal (FEMA) emergency management personnel, the U.S. Coast Guard, harbor/fleet operations (e.g., ferry service) and port security, lifeguards, fishermen, and recreational swimmers and boaters. Improved warnings and other information will be instantly transmitted to local coastal officials and municipal lifeguard units through an automated text messaging/paging database currently utilized by NYHOPS to provide coastal flood warnings [HE05].

In terms of long-term relevance and benefits, capabilities developed and lessons learned as part of the NYHOPS deployment could easily by transferred to other regions and coastal ocean observing systems as part of IOOS (nationally) and GOOS (globally). Adaptive targeting and sampling will enable *improved, autonomous, and faster* four-dimensional realization, analysis, understanding, and prediction of common coastal processes and phenomena, supporting improved understanding of the coastal ecosystem and carbon cycle as well as improved decision-making for maritime operations, hazard response, beach closures, etc.

The ocean sensor web adaptation technology developed specifically addresses the NASA Earth Science Enterprise research questions of, "*What are the consequences of climate and sea level changes and increased human activities on coastal regions*". It falls within the *Carbon Cycle and Ecosystem* and *Climate Variability and Change* Science Roadmaps, and also the *Coastal Management* priority area of NASA's ESTO Applied Sciences Program. As such, there is clear linkage and application for research communities as well as end-users such as managers, decision-makers, and policy makers. Focused, intensive, and coordinated surface and sub-surface observations of coastal events or anomalies provide greater scientific understanding through real-time acquisition of synergistic biogeophysical data sets at relevant spatio-temporal scales, and in turn enable more accurate nowcasting and forecasting in support of coastal user needs. As outlined in the NASA Strategic Plan 2006 (pg 39), sensor webs that enable autonomy and interaction of space and surface sensors is a top priority; the CARDS ocean sensor web adaptation technology enables such environmental characterization and prediction.

Relevance to AIST Objectives

In CARDS for Smart Sensing in AIST, we have designed and developed advanced information system technologies in sensor web event detection and adaptive control that satisfy the specific requirements:

• Enable new observation measurements and information products for maritime data that may be currently unavailable;

• Reduce response time to rapidly unfolding events such as storm surges, and other hazards (~spills) in the NY/NJ estuary;

• Increase the accessibility and utility of data and information via real-time, autonomous model-based episodic event detection and forecast and distribution to the scientific and user (marine fisheries, US Coast Guard, port security) communities in the NY/NY Estuary to enable/support improved benefits for research, hazard mitigation and other societal benefits;

• Reduce the cost, size, and development time for Earth science ground-based information systems (specifically NYHOPS) via autonomous resource management of energy/power that will increase system lifetime and reduce the need for manual oversight (with applicability to space systems in the future);

• Increase the scientific value (quantity and quality) of maritime observations by enabling real-time analysis of coincident remote satellite sensors from in-situ detected events;

• Produce IT components that can ultimately be integrated, infused and demonstrated on functional ocean sensor web systems such as the NYHOPS sensor web.

2. Related Work

Resource allocation is the assignment of a system *resource* toward the fulfillment of a *task* that generates a certain amount of *utility*. Usually, the set of resources is limited, causing contention among the tasks that can be completed at a given time. In the remote monitoring from space domain, the resources may be the set of sensors that are present on a satellite, the tasks may represent locations on the earth that are to be sensed, and the utility of sensing particular locations represents the expected science return [2]. In the remote sensing domain, the set of resources and tasks are often too large to be handled by general planning algorithms. In this case, specialized planning algorithms are used that take into account the specific properties of large environmental models and datasets [3].

In applications that utilize sensor networks, the set of tasks is not known in advance, but rather tasks are generated by environmental processes that cannot be predicted completely (*online* resource allocation). Moreover, resource allocation in these applications will have to be performed in real-time which preclude the possibility of executing optimal task allocation algorithms if they take too long to complete. Iterative planning is a process where a pre-computed plan is refined upon receiving new tasks. This approach is used in the allocation of satellite resources to a set of desired earth observations [2]. The planner in the system is ASPEN, which performs local search using a combination of heuristics [4]. CASPER is an online planner that is embedded in an orbiting satellite [5]. This planner is model-based. It takes as input science goals (generated by an on-board event detector) and generates a plan that is likely to lead to observations of interesting events.

3. The New York Harbor Observing and Prediction Ocean Sensor Network System (NYHOPS)

NYHOPS is comprised of a network of sensors and a model of the ocean environment to monitor and predict coastal and ocean conditions in the densely populated regions of the Hudson-Raritan Estuary and the New Jersey Atlantic Ocean shoreline [1]. The region modeled by the system is shown in Figure 2. The readings from the sensors are provided to the model of the environment, the ECOMSED/POM model [6]. ECOMSED is a hydrodynamic model that describes the physical properties of the entire water mass in the NY/NJ harbor area using a set of differential equations (representing conservation of mass and momentum, and heat transfer). The inputs to the model are ocean elevation (which depends on tides, offshore weather, cross-shelf elevation change), salinity and temperature at the open and coastal boundary of the model, and weather (air temperature, humidity, pressure, wind speed, solar radiation, cloud cover obtained from NOAA weather stations and forecasts). The model outputs are elevation, salinity, temperature, and water velocity. The model predictions are calculated over a high resolution orthogonal but curvilinear three-dimensional grid. The resolution is highest in the inland water bodies and decreases toward the open ocean. The model is run daily and the predictions (along with hindcasts) are displayed as images on a webpage.

Boundary conditions for the model are available from ground-based sensors and weather from NOAA. In addition, unmanned underwater vehicles (UUVs) may be deployed to obtain additional information. Sensors may also be attached to passing cruise ships to collect oceanographic parameters along the paths of these ships.

In the NYHOPS system, sensors that are deployed along the coast or in the NY/NJ harbor have to transmit their measurements to a central data acquisition/control computer. The distant location of the sensors with respect to this central computer requires that *remote dataloggers* act as an intermediate relay station. A datalogger (which is a PC) compresses data files, establishes a connection to the Internet via a local ISP, and pushes the data to the data acquisition server. The data transmission to the remote datalogger is through a line-of-sight serial radio modem system. A sensor can establish a 1200 baud, two-way simplex communication link with any of the remote dataloggers. Mobile sensors utilize serial cellular modems for data transmission to the remote logger. Currently, the data collection schedule is adjusted based on the power source and sampling requirements of the platform. Sites that are on the power grid can collect and transmit data at a high frequency. Typical sampling schedules consist of the measurement of up to 20 parameters that are retrieved every 5 minutes. Sensors that do not have access to the power grid measure an average of 10 parameters every 15 minutes and data is retrieved once every hour.

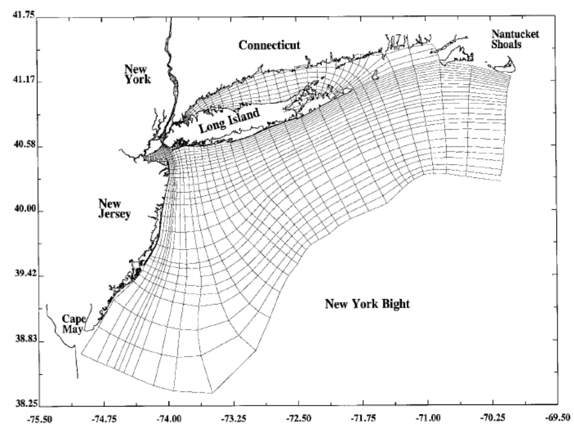

Figure 2: Output area of the ECOMSED hydrodynamic model.

4. Improving model prediction accuracy by incorporating real-time sensor measurements

The model predictions will not exactly match real-world conditions because of a variety of reasons. These include unmodeled phenomena in the ECOMSED model, approximations in the layout of the three-dimensional grid, the finite resolution of the grid, and errors in the sensor measurements that form the boundary conditions. The CARDS project describes a method by which real-time sensor measurements can be incorporated into the model outputs so as to increase the accuracy of the NYHOPS predictions.

The resolution of measurements from physical sensors is expected to be much lower than that of the hydrodynamic model. We developed a nudging assimilation algorithm that integrates point data into

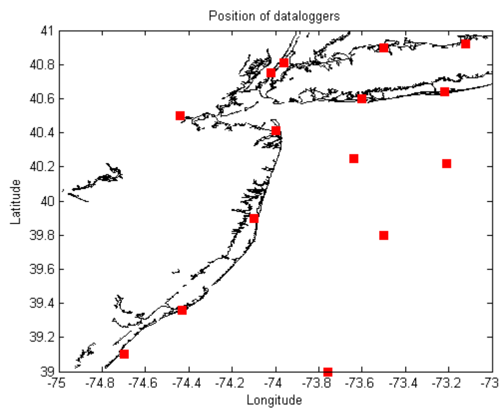

Figure 3: Locations of simulated dataloggers.

the gridded predictions. The algorithm works by identifying the closest model grid cell to a given observation location and replacing the forecast value with the observed value. We then solve the Laplace equation to "spread" the influence of the observation to neighboring cells in the grid by proportionally smaller amounts.

Physical sensors that comprise part of an embedded sensing network are limited by energy and communication bandwidth resources. Operating the sensors at their maximum sampling rates while transmitting the resulting data across the network is likely to exceed these energy and bandwidth limits. Thus, it is desirable to implement a means of regulating the operation of all the sensors (such as sampling rates) in the network so as to maximize the expected utility of incorporating the sensor data into the system output while still ensuring that the physical limitations of the sensor network (such as energy reserves and bandwidth) are not exceeded.

4.1. Model Predictive Control for Resource Management in SpatioTemporal Ocean Sensor Webs

We utilize a general mathematical control framework called Model Predictive Control (MPC) for regulating the operation of the sensors in the sensor network. MPC is an established technique for controlling complex continuous systems. MPC assumes that a model that describes how the system state responds to control inputs is available. At each control iteration, the values of the controlled inputs are obtained by solving an optimization problem that utilizes this state model. Limits on the range of the control, and other domain-specific requirements are specified naturally as equality and inequality constraints in the optimization step. This flexibility in problem specification and the ability to derive optimal control are some of the chief advantages of this control technique. Successful applications of MPC include chemical process control and resource management in the battlefield [7-10].

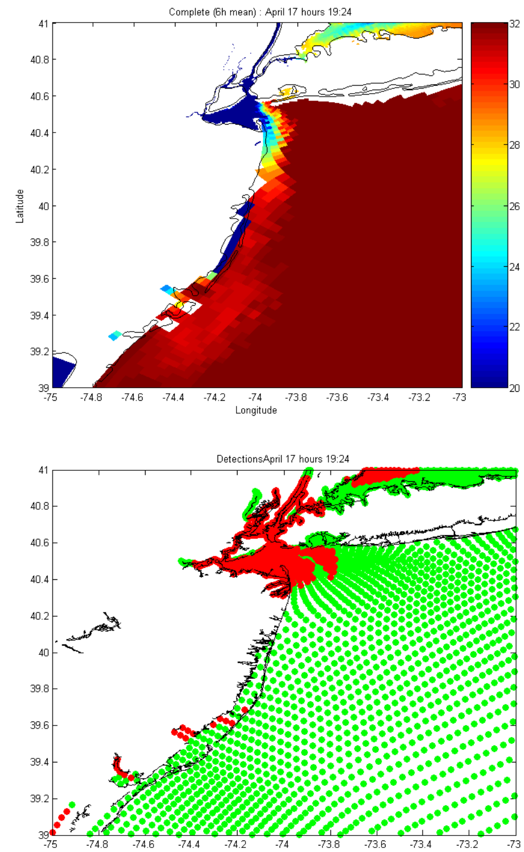

Figure 4: Top: Observations (at high spatial resolution) at one time instant. Bottom: Locations of detected events.

We designed a MPC controller that takes into account the utility of operating the sensors and the limitations of the NYHOPS network. Optimal controls are generated for (outputs of the MPC controller):

1. Sampling rates of fixed sensors
2. Positions of mobile sensors such as UUVs
3. Assignment of sensors to dataloggers

The constraints in the optimization problem represent:

1. Maximum sensor sampling rates
2. Physical limitations of the UUVs (such as speed, and energy capacity)
3. Bandwidth of the wireless communication network

A single objective function cannot model all the system components that are to be optimized. Hence, the optimal control is obtained as the solution to a series of objective functions (*multi-objective optimization*):

1. Maximize the utility of measurements from fixed sensors
2. Maximize the utility of measurements from mobile sensors
3. Minimize the energy expended in moving mobile sensors
4. Minimize the energy expended in wireless data transmission

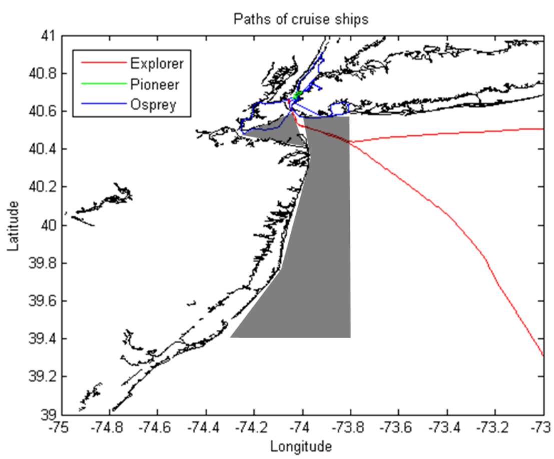

Figure 5: Paths of cruise ships and navigable areas of UUVs (shaded regions).

We have derived a statistical model to describe the utility of obtaining measurements from spatially separated sensors at different sampling rates [11]. This statistical model forms the basis for the MPC objective functions.

5. Results

True ground truth sensor observations are not available at the required resolutions throughout the modeled area. Hence we studied the end-to-end performance of the CARDS approach to improving model prediction accuracy in simulation. Sensor data was simulated by subsampling from high resolution ECOMSED model output (NYHOPS forecasts and hindcasts). The base model predictions were obtained by intentionally "compromising" the ECOMSED model, i.e., certain model parameters were set to historic values instead of real-time observations in order to increase the divergence from true observations. The locations of local universities, and a

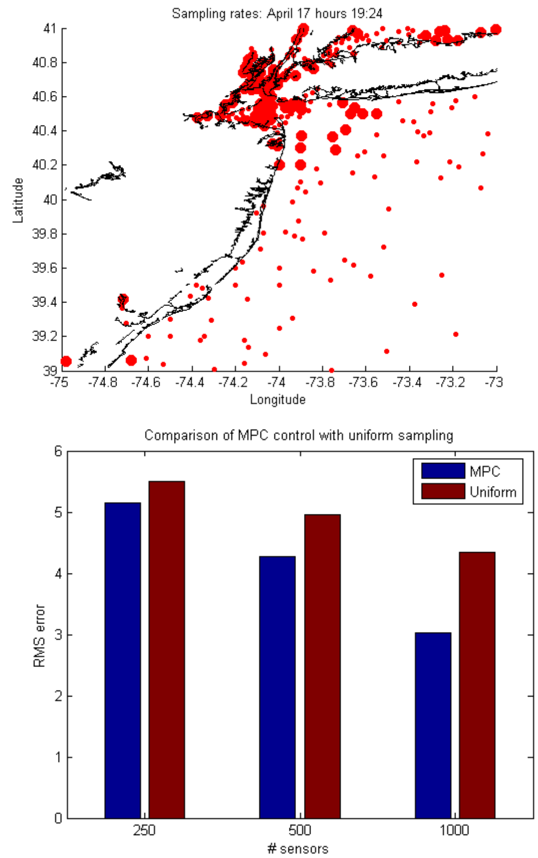

Figure 6: Top: Location of sensors. The size of the dots is proportional to the sampling rates. Bottom: Decrease in RMS error when using adaptive sampling as compared to uniform sampling.

few coastal spots were chosen as positions of dataloggers for this simulation study (Figure 3). A few of the dataloggers were also situated in the open ocean in order to keep the maximum data transmission distance between sensors and dataloggers within practical radio range. We assumed that UUVs could navigate freely in the Lower New York Bay and along the New Jersey coast. The paths of cruise ships that regularly ply in the area was available and we simulated sensor measurements along these paths (Figure 5).

5.1. Monitoring the evolution of a freshwater plume

During the week of April 15, 2007 unusually heavy rainfall caused a freshwater flooding event in the New York harbor and surrounding ocean ("Tax

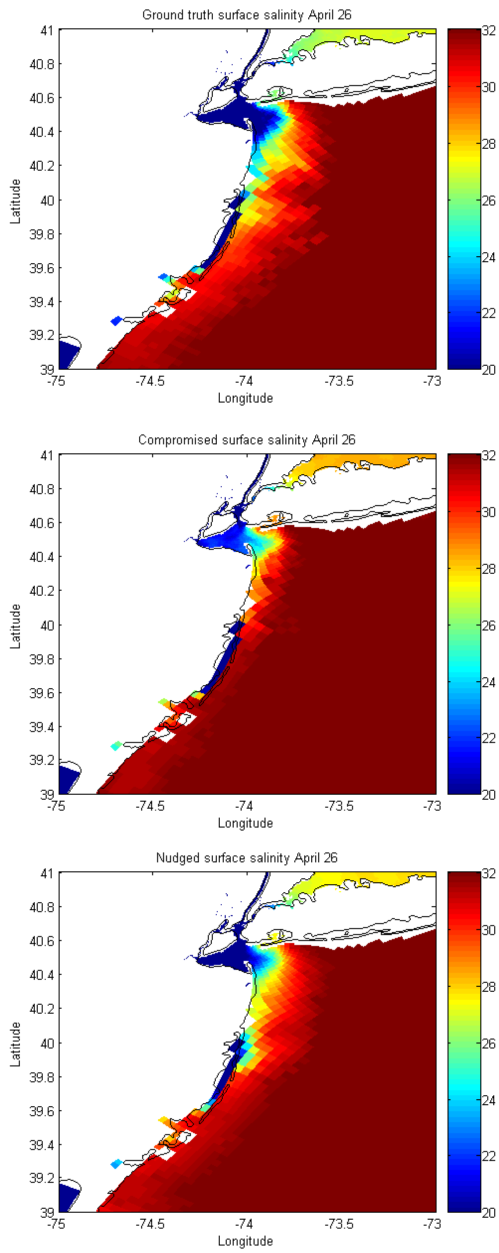

Figure 7: Top: Ground truth surface salinity. Middle: Compromised model output. Bottom: Surface salinity after assimilation.

day flood”). This caused a freshwater plume to form in the New York Bay and spread out into the open ocean. Such events may carry pathogens from overwhelmed treatment plants into the coastal ocean. For this study, we set the flow rates of freshwater into the ocean in the ECOMSED model to their historic median rates. This compromised ECOMSED model did not predict the freshwater plume but the simulated sensors observed the plume (as these were obtained by subsampling the uncompromised ECOMSED model output from the NYHOPS forecasts and hindcasts).

We implemented an event detection algorithm to determine those (time varying) regions in the modeled area that will benefit the most from assimilation of sensor observations in indentifying the freshwater plume. To demarcate the extent of the plume we used the difference in surface salinity from historic expected levels. Sensors observing salinity values that were beyond one standard deviation from the historic mean were immediately designated to be in the critical region (Figure 4).

The locations of the simulated sensors are shown in Figure 6. The size of each dot indicates that sensor’s optimal sampling rate. The decrease in root mean square error (RMSE) using our adaptive sampling approach is compared with that achieved with uniform sampling in Figure 6. The uncompromised ECOMSED predictions which correctly modeled the plume served as ground truth.

The results of assimilating surface salinity are shown in Figure 7 along with the original compromised model prediction and the simulated ground truth values. The surface salinity after assimilation matches the ground truth significantly (the RMSE values are shown in Figure 8).

The effect of assimilating sensor data from the available UUVs (whose paths are optimized by our MPC controller) and the passing cruise ships is shown in Figure 8. The “No Nudging” case shows the RMS error of the compromised ECOMSED prediction. The other cases include the different available sensor observations using the nudging algorithm. As expected, increasing the number of sensor observations that are assimilated decreases the RMSE. However, the relative benefit of using a mobile asset depends on its location. For instance, one of the ships moves in the Upper New York Bay, an area where there are few sensors. Hence, assimilating data from this ship leads to a large decrease in RMSE.

6. Future Work

The sensor network adaptation technique described in this work can be generalized to respond to sensor observations from a variety of sensors and to calculate optimal control for multiple entities. In particular, sensor observations can be obtained from remote sensing satellites. The MPC controller can also be used to calculate as part of its output locations in the

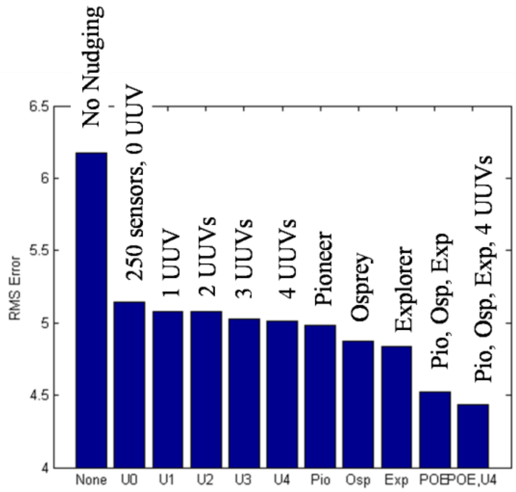

Figure 8: Decrease in RMS error with increasing number of UUVs and cruise ships (named *Explorer, Pioneer*, and *Osprey*).

environment which are expected to provide maximum science return. This can then be used to autonomously generate observation tasks for satellites such as the EO-1.

7. Conclusions

The paper demonstrated a framework for resource management in ocean observation networks. The technique is general enough that it can produce control for static sensors, optimal paths of mobile sensors, and wireless transfer of sensor data. The control technique adapts these sensor and communication resources to changes in the ocean environment. The changes in the environment can be calculated from a variety of data sources. We demonstrated how static sensor measurements, data from UUVs and from passing ships can be assimilated into the outputs of a hydrodynamic ocean model to increase the prediction accuracy of the system forecasts. The CARDS approach can be generalized to accept data input from remote sensing satellites and to generate observation tasks for satellites.

8. Acknowledgment

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