A Surveillance Application of Satellite AIS
Utilizing a Parametric Model for Probability of Detection

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Abstract: The question of having sufficient surveillance capability to detect illicit behaviour in order to inform decision makers in a timely fashion is of the ultimate importance to defence, security, law enforcement, and regulatory agencies. Quantifying such capability provides a means of informing asset allocation, as well as establishing the link to risk of mission failure. Individual sensor models can be built and integrated into a larger model that layers sensor performance using a set of metrics that can take into account area coverage, coverage times, revisit rates, detection probabilities, and error rates. This paper describes an implementation of a parametric model for Satellite Automated Identification System (S-AIS) sensor performance. Utilizing data from a real data feed, the model was able to determine the percentage of uncorrupted S-AIS messages and the probability of detection of at least one correct S-AIS message received during an observation interval. It is important to note that the model implementation was not actively calculating the effect of message overlap based on satellite altitude and footprint width, or reductions in collisions due to signal de-collision algorithms.

1 INTRODUCTION

The awareness and associated tracking of maritime vessels approaching and within a country's territorial waters (TTW) and its exclusive economic zone (EEZ) are necessities for the enforcement of environmental and commercial laws and regulations, as well as national security and the protection of public safety. This makes maritime domain awareness (MDA) a national priority. There are two aspects to MDA: the quality and quantity of data to collect and fuse, and the reporting/prediction metrics that are used to gather the information into a quantifiable, comparable fashion for decision support. The former is well recognized as an issue for data analytics, data fusion, and big data research topics. The latter falls under the more traditional operational research umbrella, and will be discussed in this paper. The data analytics problem is beyond the scope of this discussion; for a more detailed treatment of data collection requirements for MDA, see Horn *et al.* (2016) and references therein.

Metrics that can be used for historical reporting and forecasting of upcoming activities are of particular interest at the operational level because they provide critical information to military decision makers about the use of surveillance capabilities, such as:

- Will the surveillance capabilities provide sufficient means to detect illicit behaviour?
- What is the likelihood that illicit behaviour would go undetected?
- Will the surveillance capabilities provide sufficient temporal and spatial coverage of the area of responsibility (AOR) to be able to inform decisions in a timely fashion?

The answers to these questions are of the ultimate importance to defence, security, law enforcement, and regulatory agencies, as they provide means of informing asset allocation, as well as establishing a link to the risk of mission failure for given capability sets.

The purpose of this research is to select one surveillance sensor – in this case, the Automatic Identification System (AIS) – to model the performance of, and use it as a test case towards

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building a more complex, layered model of surveillance capabilities. This will enable reporting and planning for the given capability sets.

This paper is organized as follows. Section 2 provides a brief description of how AIS functions, the utility of the selected sensor, and the inherent complications when trying to model such a sensor. Section 3 describes the simplified performance model chosen and the associated advantages of using such a sub-model within a larger model. Section 4 illustrates how the sensor and performance model were implemented, and provides a test case using real world data from an AIS feed to compute performance parameters. Section 5 discusses some of the limitations of the current model and implementation, and presents proposals for future work. Section 6 concludes the paper.

2 THE AUTOMATIC IDENTIFICATION SYSTEM

One sensor that is now commonly exploited for MDA is AIS, which is a self-reporting system that was designed for enhancing the safety of navigation at sea. AIS transponders are mandated by the International Convention for the Safety of Life at Sea (SOLAS) Convention, 1974 (International Maritime Organization, 2015) for all ships over 300 gross tonnage, all passenger-carrying vessels, and can be used by other vessels on a voluntary basis.

Vessel-mounted AIS transponders are broken into two types. Class A transponders are required on the mandated vessels described previously. Class B transponders are a lower power, less expensive technology which transmit less frequently than their Class A counterparts, and are often used on smaller vessels. It can be estimated that AIS is utilized on anywhere from approximately 400,000 to over 550,000 ships, navigational aids, base stations, and other sources (including active and decommissioned vessels), depending on the data provider (myShipTracking, 2016; MarineTraffic.com, 2016). While the fraction of active Class A versus Class B sources are not directly reported, this does provide a sense of the volume of information received by tracking networks when ships are reporting anywhere from 2 seconds to 6 minutes apart (International Telecommunications Union, 2014).

2.1 Sensor Utility

Terrestrial-based tracking networks provide a means of continuously monitoring so equipped ship traffic within the detection range of the shore-based stations. However, AIS signals were found to be detectable from satellite-based receivers as well. Some of the main limitations with satellite AIS (S-AIS) are the amount of sensor coverage and the revisit rates of the satellite, which can be mitigated in part by monitoring from multiple satellites. So, while coastal AIS systems are advantageous for monitoring of the TTW and a fraction of the EEZ – with distances depending on very high frequency (VHF) ducting properties (Tunaley, 2011a), S-AIS has moved to the forefront of technologies for wide-area surveillance at high refresh rates for reach over almost any AOR.

S-AIS is usually employed in conjunction with other sensors, such as coastal radar (Canadian Coast Guard, 2016), high-frequency surface wave radar (Vesecky *et al.*, 2009), satellite-based synthetic aperture radar (Guerriero *et al.*, 2008), or visual identification (or other onboard sensors) using maritime or aerial assets (Busler *et al.*, 2015). This helps to mitigate some of the known issues with data quality (such as signal errors, technical installation or input errors, or spoofing (Bošnjak *et al.*, 2012)).

2.2 Modelling Complications

Technically, however, S-AIS also suffers from further complications due to the simultaneous reception of a high number of messages within the large reception footprint in conjunction with the AIS communication standard (International Telecommunications Union, 2014). The design of the AIS message system into discrete, fixed width slots limits the reception of messages at the receiver, and the sheer volume of the AIS message traffic produces a high probability of message collision (i.e., message arrivals within the same time slot). On-board processing (OBP) of messages cannot fully resolve such collisions, and as a result, the first pass detection is low (exactEarth, 2012) when ship traffic is dense. While much can be done in terms of antenna design and signal processing (Yang *et al.*, 2014; Yang *et al.*, 2012; Picard *et al.*, 2012) to reduce these effects, there still exists a significant impact on the sensor's overall detection performance.

Some providers have chosen to downlink all messages to ground stations for more efficient spectrum de-collision processing (SDP) (Macikunas and Randhawa, 2012). Algorithms have been proposed and/or implemented (e.g., Cowles *et al.*, 2014; Cherrack *et al.*, 2014) to increase the detection performance; however, the time latency of the data is dramatically increased (Meger, 2013).

3 SIMPLIFIED S-AIS MODEL

For the purposes of historical reporting and forecasting of upcoming activities at the operational level for defence primarily (but also including security, law enforcement, and regulatory agencies), the following considerations and assumptions are made:

- Any model must run in a practical amount of time so as to be able to provide timely and meaningful decision support (typically viewed as 1-2 days for short turn-around analyses). Thus, simpler is better;
- When representing the capabilities of a system that link to the risk of mission failure, often the “worst case scenario” is chosen to represent the ultimate limit of the system’s capabilities. So, for example, if ground stations were unable to perform SDP for some reason, then OBP would be considered the minimum capability provided. It also provides a consistent model and assumption set across all S-AIS providers, since some perform SDP and some perform OBP;
- From a reporting/forecasting standpoint, the timeslots of individual messages are unknown (data not provided), and so the de-collision process cannot be reproduced and modelled directly. While the signal de-collision process can be simulated, it is easier to implement a direct relationship between the number of ships and the probability of detection; and
- Since not all AIS providers utilize SDP, it is assumed that a generic model that can be applied across any provider would provide more utility. It could later potentially be scaled to account for SDP.

3.1 Single Sensor Model

In order to be able to quantify the ability of a collection of disparate sensors, each with their own area coverages, coverage times, revisit rates, detection probabilities, and error rates (false positives, false negatives, bit rate errors, etc.), a set of metrics that can take all of these factors into account is required. Individual sensor models can be built and integrated into a larger model that layers sensor performance over an AOR for a comprehensive capability to report on historical coverages and test out future surveillance plans. High fidelity tools, such as the Systems Tool Kit (STK), can be used to build such a model. The satellite selected for the application here was exactView-1, one of the exactEarth™ constellation of satellites.

Modelling of the coverage of active or non-cooperative passive sensors (i.e., independent of the cooperation of a vessel) in a software package such as STK is generally straightforward; however, modelling of cooperative sensors such as AIS can be more challenging. While all vessels must be represented as objects in a modelled scenario in STK, this does not mean that they can or should be detected by sensors at all times. Different vessels transmit AIS messages at different times and at different rates; therefore, the sensor cannot automatically assume it can “see” the vessel all of the time.

3.2 Sensor Detection Performance

Høye (2004) quantified the parametric relationship between the number of ships in the S-AIS sensor’s field of view (FOV) and the probability of detecting a single ship; however, it was assumed that message collisions could not be de-conflicted. Tunaley (2011b) later showed that the probability of extracting an uncorrupted message, γ, from the simultaneous arrival of another singleton message can be derived in the presence of thermal noise, interference from neighbouring channels or even interference in the same channel from terrestrial transmitters (Eq. 1).

$$\gamma = \gamma_o e^{-\lambda\tau_o(1-q)(1+s)} \quad (1)$$

The explanations for, and the values of the parameters in Eq. (1) from (Tunaley, 2011b) for a satellite at 800 km altitude are provided in Table 1. Høye (2004) reports the difference in the s values between 600 km and 800 km altitude as 0.0382, while the difference in the s value between 800 km and 1,000 km altitude as 0.0248. Therefore, the average difference between each 1 km of altitude is ~0.0002. This means the 5 km to 40 km offset in the STK exactView-1 satellite object’s altitude has a negligible effect on the 0.6744 value of s for a satellite with 800 km altitude. As a result, a fixed s value was used for the initial model (MacNeil, 2015).

Table 1: Equation parameter definitions.

Parameter	Name	Value
γ_o	Probability of receiving an uncorrupted message at the input system regardless of collisions	0.2683
λ	Mean rate of random messages arriving	Eq. (2)
τ_o	Length of slot (s)	0.0267
q	Probability that an additional signal does not corrupt the message	0.904
s	Effect of range overlap	0.674
M	Number of ships inside the ships cell	Assumed negligible
n_{ch}	Number of VHF channels	2
ΔT	Mean time between message transmissions (s)	Calculated

The mean rate of message arrival (λ) as a function of number of ships (N) in the FOV is given in Eq. (2), with parameter values also provided in Table 1.

$$\lambda = \frac{N - M}{n_{ch}\,\Delta T} \tag{2}$$

Substituting λ from Eq. (2) and all parameter values from Table 1 in Eq. (1) yields Eq. (3).

$$\gamma = \gamma_o e^{-\frac{N}{2\,\Delta T}\tau_o(1-q)(1+s)} \tag{3}$$

$$\gamma = 0.2683 e^{(-0.002145)\frac{N}{\Delta T}}$$

The probability that at least one correct AIS message will be observed during a given interval (T_{obs}) (Tunaley, 2011b) is provided in Eq. (4) after substituting in Eq. (2).

$$p = 1 - \left(1 - \gamma_o e^{-\frac{N}{2\Delta T}\tau_o(1-q)(1+s)}\right)^{T_{obs}/\Delta T} \tag{4}$$

3.3 Model Implementation

The parametric model was implemented using STK to perform its satellite modelling and line-of-sight (LOS) calculations (MacNeil, 2015). The MATLAB scripting language was also selected for use, as it integrates directly with STK and automates the execution of STK commands. The model implementation was driven by a series of MATLAB scripts to perform LOS analysis in STK between a satellite sensor, representing exactView-1 AIS, and three predefined AORs (shown in white in Figure 1). These line-of-sight analyses are referred to in STK as access calculations.

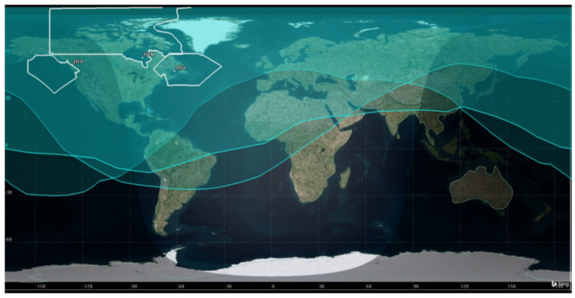

Figure 1: Three Canadian AORs (white outlines) and the exactView-1 AIS sensor FOV (cyan overlay) over time when access is available to each AOR.

The parametric model was designed to take geographically-tagged JavaScript Object Notation (GeoJSON) S-AIS messages from the exactEarth™ satellite feed and calculate the probability of extracting an uncorrupted message when the exactView-1 AIS sensor FOV has access to an AOR. One day's worth of S-AIS position reports (approximately 4.5 million messages) were filtered for Class A messages only. To reduce the problem set, the target areas were selected by the union of all areas covered by the exactView-1 AIS sensor footprint when the sensor had access, or LOS, to each of the AORs separately during the defined scenario period. This left approximately 2.2 million position reports to process. The execution of the model was then broken down into three sequential operations (MacNeil, 2015):

1. Partitioning and reformatting S-AIS position reports into separate ship files based on unique Maritime Mobile Service Identity (MMSI) numbers;
2. Creating the relative STK ephemeris and interval constraint files for each ship; and
3. Analyzing the STK satellite-to-ship access data for each AOR, and collating the data to determine the probability of extracting an uncorrupted message for each observation period.

Additional algorithm implementation details are provided in the paper's appendix.

4 RESULTS

The partitioning and reformatting of the S-AIS position reports took 14.3 hours to complete on a 3.20 GHz Intel® Core i5-4570 with 8 GB (3.18 GB usable) RAM and an Intel® HD Graphics 4600 processor graphics card. The script produced over 61,000 partitioned S-AIS ship data files. The script excluded, or dropped, message rows that were not Class A position report messages.

The execution of the script to create the STK ephemeris and interval constraint files for each ship took 7.5 hours to complete. The script produced over 43,000 files of each type. The script excluded, or dropped, partitioned ship files that existed outside of all three AOAs.

The creation of the STK scenario and analysis of the satellite-to-ship access took 7.7 hours to complete. Each sensor FOV included approximately 29-39,000 individual ship objects. During the scenario, there were 11-14 access intervals for the AORs. Each access interval was treated as a separate observation period for the purposes of the following results.

For the scenario considered, the execution time was relatively reasonable. However, it may prove challenging to remain within practical time limits when integrating further sensors into the mix, depending on the amount of computations that can be leveraged between sensors. One way to speed up the computations would be to take advantage of MATLAB and STK's parallel processing features; however, both require specialized licensing.

4.1 Uncorrupted Messages

For each access interval, the probability of receipt of an uncorrupted message was calculated using Eq. (3). Given that the duration of each access interval varies, as does the number of messages received, the mean time (ΔT) between messages could not be considered to be constant. ΔT was calculated using the total access duration divided by the number of messages received for the given interval, Figure 2 results, where the data points for the access intervals are shown individually (diamonds) on plots of the function from Eq. (3). The function plots match the access interval ΔT values, while varying the number of ships in the FOV. As the number of ships in the FOV increases or the time between messages decreases the probability of receipt of an uncorrupted message decreases. Thus, as more ships that exist within the FOV and transmit messages more often, the more likely the signal collisions are to cause corruption in the messages.

Previous implementations (such as Tunaley, 2011b; Parsons *et al.*, 2013) assume that the mean time between messages and the observation time are fixed. Here, a single pass of the satellite is utilized over a variable observation time frame, as determined by the sensor's access time to each

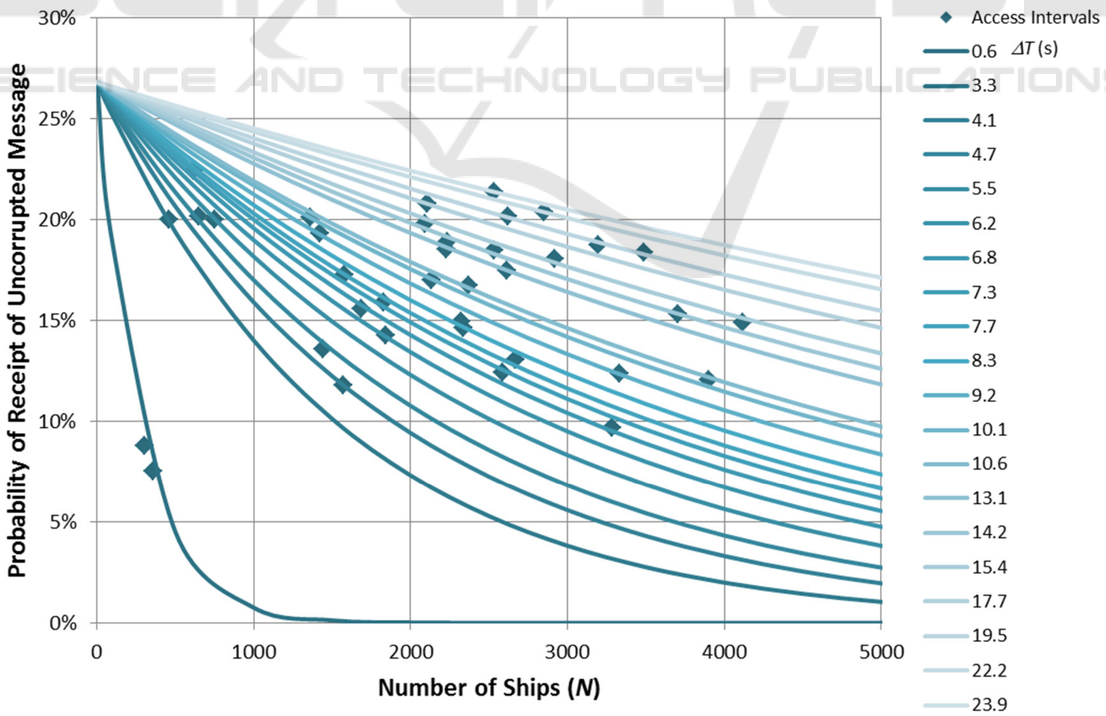

Figure 2: The fraction of messages that are uncorrupted as a function of number of ships in the sensor FOV and the mean time between messages.

AOR. This time frame is significantly longer than the average time a ship is visible within the sensor footprint. The mean time between messages is then calculated based on the received data within that time frame. This cross validates the equation parameters from Table 1, as well as the basic model for on-board processing system performance.

4.2 Probability of Detection

From Eq. (4), $T_{obs}/\Delta T$ is essentially the count of the number of detections in the FOV over the duration of the access interval. Because the FOV is large and the access duration is long, the number of detections observed is in the thousands or tens of thousands. As a result, this term tends to zero, resulting in a near 100% probability of detection of at least one uncorrupted AIS message from any given ship in the FOV.

While edge effects from the shape of the footprint (which is a circular beam projected at an angle over a spherical surface) will reduce the amount of time some ships will remain observed, the observed time would have to be reduced by more than 92% to see any less than 99% probability of detection of at least one correct AIS message.

5 DISCUSSION

Since the purpose of this work was to create a simple preliminary model that could be used as the basis for further integrated model development, there were some noted issues that are planned to be addressed in future work.

5.1 Message Quantity and Quality

The GeoJSON data is contained in a large text file that is organized according to a contact identification column and not by date/time stamp, which makes it difficult to perform read search and sort operations in MATLAB. Initial file parsing would likely be better suited to database operations either through a performed with Structured Query Language (SQL) commands through either a Python or C++/C# application (MacNeil, 2015). An application written in Python would be easier to update and modify since it is a dynamically typed scripting language, and could be integrated with technologies such as ArcGIS for geo-filtering of data points. Programs written in C++/C# are compiled to native machine code, and can be very computationally quick. An application written in C# would also easily integrate with the STK Integration plugin.

Naturally, since the topic deals with corrupted AIS messages, the quality of the data from the AIS feed can be an issue to parse. From the data, it was noted that there were objects that travel semi-erratically across the globe, ship MMSIs which consistently reported the same, or very similar, invalid positions, and objects which contain a single invalid, potentially corrupt message. The first step in helping to resolve some of these issues would be to filter the AIS messages based on Tunaley (2013). This would restrict the MMSIs to valid ship codes of interest. By extending the model to more satellites and to global coverage, location-specific issues should also be resolved.

It is also important to note that the precision of the GeoJSON formatted S-AIS data's report and received date/time is to the second. The time length of a single AIS transmission time slot is 0.0267 seconds. Thus, a small amount of error is introduced when parsing the data.

5.2 Model Refinement

At the moment, the values for the parameters in the governing equations are primarily taken from Tunaley (2011b). The next level of refinement to the model would be to determine the current values for s and q based on the scenario satellite data instead of using a constant value. While a brief analysis of the s value revealed that the difference between a fixed and dynamic value is small; it represents an increase in fidelity of the model and supports extensibility to other satellites. This would require implementing Høye's (2004) model to determine the value based on STK's exactView-1 satellite object's altitude and the partition of the satellite's sensor detection area.

As mentioned in Section 4.1, the model and scripts should be modified to support the entire exactEarth™ satellite constellation. This would enable the computation of the performance of the sensor system as a whole.

As well, the model and scripts could also support global coverage analysis. This would require the removal of the dependency on the AOR access times from the current model and the addition of another time analysis metric (MacNeil, 2015).

5.3 Model Integration

It is intended that, once the entire satellite constellation is modelled, this becomes a sub-model in a larger, layered approach to surveillance capability planning and reporting. Thus, rather than trying to compare apples to oranges with active/passive versus co-operative sensors, the overall performance of the S-AIS sensor system can be utilized in a simplified fashion to compute the probability of detecting ships. Other sensors and platforms can be integrated over various time frames to determine what combination of capabilities provides sufficient temporal and spatial coverage of the AOR to meet the decision-makers' requirements.

6 CONCLUSIONS

A parametric model (Tunaley, 2011b) for S-AIS senor performance was successfully implemented in STK. Utilizing data from the real S-AIS feed, the model was able to determine the percentage of uncorrupted AIS messages and the probability of detection of at least one correct AIS message received during an observation interval for a one-day scenario period. This model provided a reasonable start towards building a more complex, layered model of surveillance capabilities for reporting and forecasting for defence security, law enforcement, and regulatory applications.

The implementation utilized real-world data to cross-validate the model assumptions and application over a wide variety of inputs. It is important to note that the model implementation was not actively calculating the effect of message overlap based on S-AIS sensor altitude and footprint width for the different satellite altitudes during its orbit. Although an analysis of the effect of message overlap revealed that the difference between the static and calculated values would be minor; further model refinements should still take such details into account. The model and scripts serve as a foundation for future improvements and extensions in both the scope of the model and the performance of the implementation.

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APPENDIX

The parametric model is written in MATLAB as a series of steps (Figure 3) that process the selected user input data, perform all necessary conversions, and control the execution of STK to compute the LOS calculations necessary to support computation of the probability of reception of an uncorrupted message given the number of ships in the sensor's FOV over a given period of time.

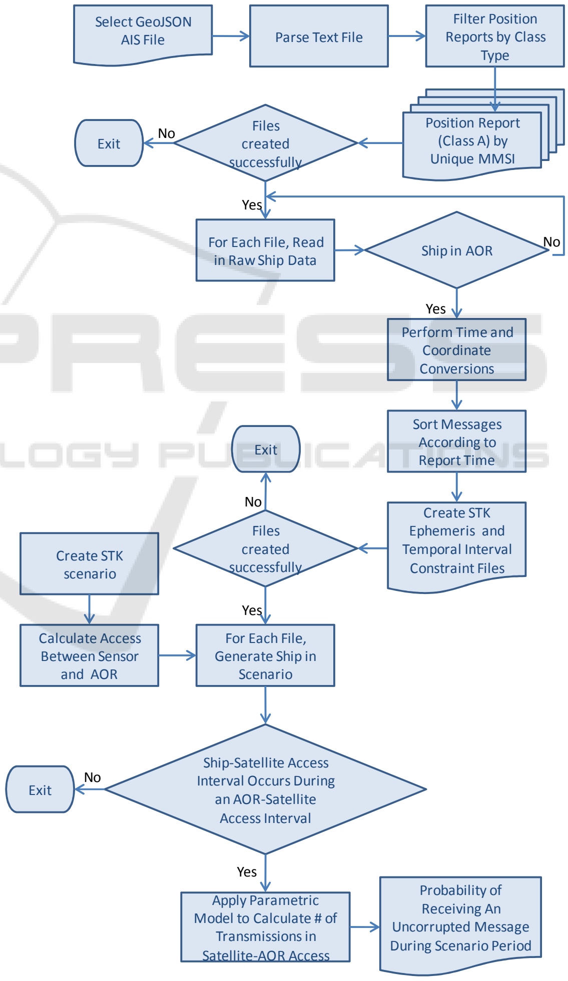

Figure 3: Parametric model implementation in MATLAB.