BIG DATA ANALYTICS FOR THE MARITIME INTERNET OF THINGS

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LARUS TECHNOLOGIES

Event : Artificial Intelligence for Insights into Regulations (October 19, 2018)

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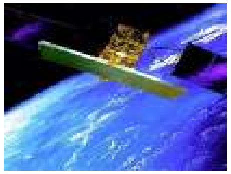
uOttawa

Overview

- About Larus Technologies
- Project Objectives
- Technology Definition
- Technology Solution
- Research Challenges
- Project Details
- Scenario Overview and Definition
- Publications

LARUS TECHNOLOGIES

Larus Technologies est. 1995



- Wholly owned Canadian engineering and product company
  - Over 20 years of experience in defence and public safety awareness
  - Specializing in **predictive analytics** and **decision support software** products
  - NATO Secret FSC, Controlled Goods Program Registered
  - Protected B level security

- Products and research capabilities in computational intelligence (CI) and predictive analytics for:
  - National and Public Security and Safety Systems
  - Domain Awareness (Sea, Land, Air, Cyber)
  - Command and Control Decision Support

- Recognized leaders in CI and information fusion research and product development
  - ***NATO Communications and and Information Agency (NCIA) Top Innovator 2017***
  - ***NSERC Synergy Award for Innovation 2016 (Small and Medium-Sized Companies)***
  - ***IEEE CI Society Outstanding Organization Award 2015***

Project Objectives

- Project Thesis
  - The exploitation of the tidal wave of sensor/human data emitted by a myriad of maritime entities (or actors)
    will improve both **internal** and **collaborative** processes for mIoT-related organizations

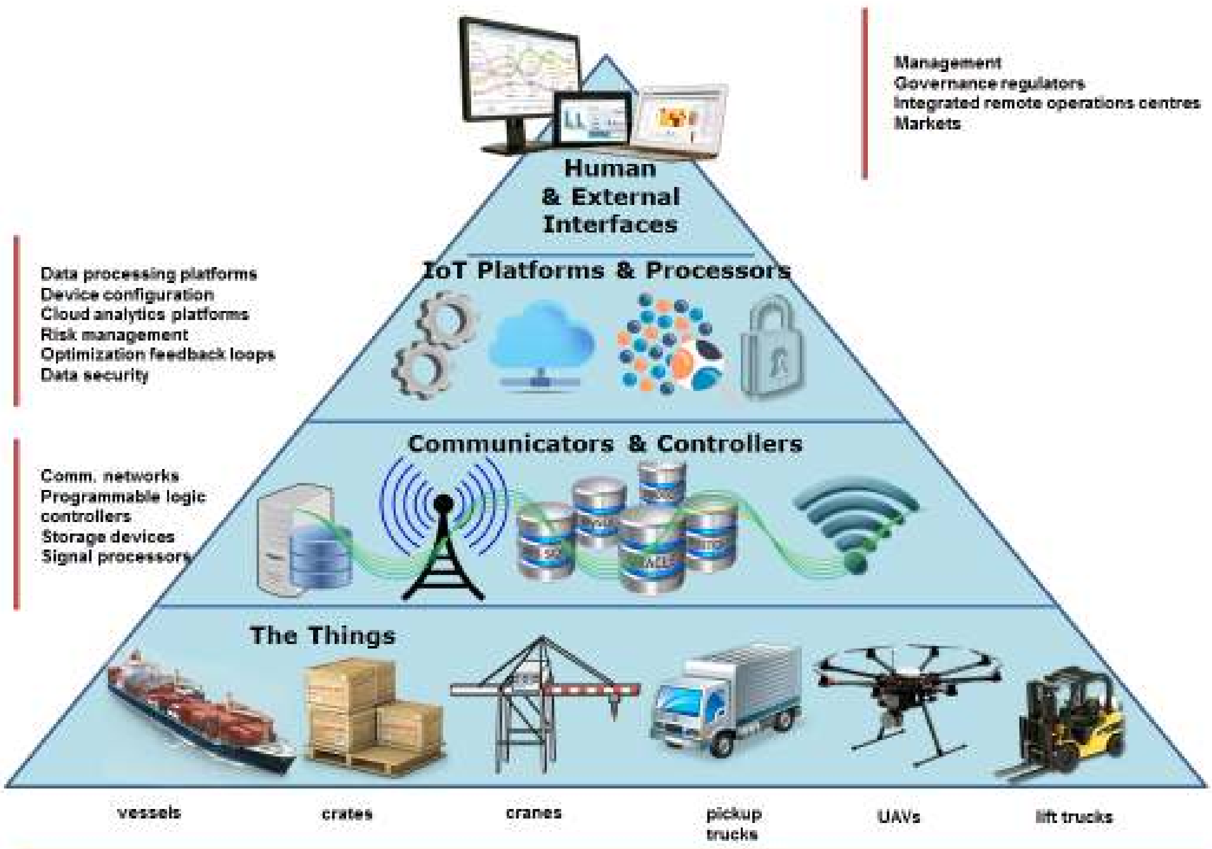
- Technical Objectives
  - To provide decision support to maritime organizations and stakeholders by applying **Machine Learning** and **Computational Intelligence** (CI) techniques, namely fuzzy systems, traditional/deep neural networks and evolutionary optimization algorithms within Big Data frameworks such as Hadoop and Apache Spark.
  - To validate the use of the above formulation in the context of maritime supply chain optimization

- Commercial Objectives
  - To integrate real-time maritime supply chain optimization capabilities into the core of Larus' Total::Insight™
    Decision Support System (DSS)
  - To market Total::Insight's novel and differentiating features in a maritime IoT operational environment

Technology Definition

- Big Data (BD) and Internet of Things (IoT) are becoming well-established paradigms
  - However their application to the maritime domain is still in its infancy
  - “Datafication” of maritime entities constitutes the backbone of the maritime IoT (mIoT)
    - cranes, crates, berths, boats, aircrafts, pickup trucks, siloes, etc.
- Maritime operations are cast into the BD realm
  - **Volume**: more descriptive types of sonar scans, higher-resolution radar images, information received from other vessels
  - **Velocity**: frequent radar scans or Automatic Identification System (AIS) reports
  - **Variety**: various sensor systems are installed on the vessels
  - **Veracity**: not all sensing systems are equally reliable, e.g., AIS can be intentionally spoofed to transmit fake information
  - **Variability**: the reported information is affected by the dynamics of the maritime region and by organizational decisions

Technology Solution (1): An mIoT architecture



Technology Solution (2): Four strategic research directions

1. High-level and context-aware information fusion [HLIF]

- Helps make sense of the multi-sensor, multi-type, rapidly-arriving, sizeable data streams emitted by the mIoT entities
- This involves securing access to both publicly available and proprietary data sources of multiple
  maritime-related organizations
  - e.g., weather advisories such as Environment Canada, maritime shipping companies, truck shipping companies, port authorities, etc
- Then it performs a centralized (i.e., server-based) pre-processing and high-level fusion of this information to arrive at a Recognized Maritime Picture (RMP) and then perform:
  - Impact Assessment (Layer 3 Fusion) to determine the most suitable responses to the events detected in the mIoT network
  - Process Refinement (Layer 4 Fusion) to determine the best resource allocation and asset configuration that helps prevent risky situations in the future.

Technology Solution (3): Four strategic research directions

2. Fog computing [FOG]

- a new paradigm that shifts the fusion and analysis capabilities closer to the data sources
- it alleviates the communication and processing overhead when this is done at the server side
- this direction involves identifying:
  - the algorithmic workflows that can be offloaded to the sensing nodes themselves
  - the hardware/software requirements needed on each node to ensure an efficient processing of these data streams

Technology Solution (4): Four strategic research directions

3. Machine-to-machine communications [M2M]

- to propagate data, insights and decisions through the mIoT network
- this includes investigating appropriate communication protocols that ensure:
  - the privacy and confidentiality of the transmitted information
  - the scalability and efficiency of the mIoT network

Technology Solution (5): Four strategic research directions

4. Decision support systems [DSS]

- goal: to present upper management, decision makers and users in general with the outcomes of the data-driven analysis
- this direction heavily hinges on selecting:
  - high-level information constructs (alerts, anomalies, trends, courses of action, behavioral patterns, scheduling options, etc.) and
  - appropriate Big Data visualization tools to present the analytics results to a particular audience
    - e.g., port managers, network operators, fleet personnel, and the like

Project Details (1): Timeline and Funding Sources

- Timeline (24 months)
  - January 2017 – January 2019
  - 7 phases/milestones
    1. Literature review
    2. Data model, hard/soft sensor data acquisition and interface design & development
    3. Algorithm design & development
    4. Algorithm empirical evaluation
    5. Scenario design and development
    6. Total::Insight integration and testing
    7. Final report and presentation

- Funding Sources
  - Ontario Centres of Excellence (OCE)
  - Natural Sciences and Engineering Research Council (NSERC)
  - Larus Technologies

Project Details (2): Team

- University of Ottawa
  - Prof. Emil Petriu, Principal Investigator (PI)
  - Dr. Roman Palenychka, Research Scientist (PDF, HLIF + Video Analytics)
  - Dr. Ibrahim Abualhaol, Research Scientist (PDF, HLIF)
  - Ms. Fatemeh Cheraghchi, PhD student (HLIF)
  - Mr. Alex Teske, MSc. Student (DSS)
  - Mr. Nicolas Primeau, MSc. Student (M2M)
  - Mr. Ashwin Panchapakesan, Research Associate / Ph.D. Student (HLIF, FOG)
- Larus Technologies
  - Dr. Rami Abielmona, VP Research & Engineering (R&E)
  - Dr. Rafael Falcon, Project Manager (PM)
  - R&E and Software Development (SD) team members as needed

Project Details (3): Available Computing Infrastructure

- SOSCIP (Southern Ontario Smart Computing Innovation Platform):
  - Granted 2-year access to the following platforms
    - Blue Gene/Q (BGQ) Platform [based at University of Toronto]
      - a highly dense and energy-efficient supercomputer built around a system-on-a-chip compute node with a 16-core 1.6 GHz PowerPC®-based CPU with 16 GB of RAM
      - well-suited for large-scale, distributed applications that can use 1,024 cores or more at a time and require low-latency, high-bandwidth communication between processors
    - Cloud Analytics Platform [based at University of Western Ontario]
      - Canada's first research-dedicated cloud environment, combining cloud computing with advanced analytics software
      - ideal for complex data analysis, such as statistical weighting and ranking, managing and streamlining large data volumes from multiple sources, and data mining

Project Details (4): Available Computing Infrastructure

- SOSCIP (Southern Ontario Smart Computing Innovation Platform):
  - Agile / FGPA Computing Platform
    - First cloud-based agile computing research environment in Canada which uses Field-Programmable Gate Array (FPGA) cards to accelerate software running on high-performance computers
  - SOSCIP GPU Cluster [based at University of Toronto]
    - SOSCIP GPU Cluster consists of of 15 (1 login/development + 14 compute) IBM Power 822LC "Minsky" Servers each with 2x10core 3.25GHz Power8 CPUs and 512GB RAM
    - Each node has 4x NVIDIA Tesla P100 GPUs each with 16GB of RAM with CUDA Capability 6.0 (Pascal) connected using NVlink

Scenario Overview

- Three scenarios were considered throughout the project:

1. Scenario 1 [intra-organizational]
   - To allow a freight ship company to keep track of its fleet of freight ships and identify (in a risk-aware fashion) those potentially disruptive events (i.e., active weather, piracy attempts, damaged cargo, unexpected delays) in their shipping schedule.
   - To allow the freight ship company to respond to these events in a way that minimizes cost and maximizes operational efficiency

2. Scenario 2 [inter-organizational, 2 organizations]
   - Similar to scenario 1 but adding a Port Authority (PA) and investigating the repercussions these events will have on the PA

3. Scenario 3 [inter-organizational, 3 organizations]
   - Similar to scenario 2 but adding a Trucking Company (TC) and investigating the repercussions these events will have on the TC

Scenario 1 Definition

1. A freight ship company X (e.g., Maersk) was selected for analysis
2. Real-time AIS feeds for all ships in X's fleet within a certain area of interest (AOI) and period of interest (POI) are available through Larus clients
3. Adverse events were simulated
   - active weather conditions
   - piracy attempts
   - damaged cargo
   - unexpected delays
4. Larus RMF provided a risk-aware view of situational elements (Level 2 Fusion) that affect X's operational efficiency
5. Larus RMF provided the automatic generation of multiple candidate responses (Level 3 Fusion) to mitigate the risky events
   - new path generation
   - resorting to law enforcement
   - etc.

Scenario 2 Definition

1. Multiple freight ship companies X_1, …, X_n and a port authority Y were selected for analysis
2. Real-time AIS feeds for all ships in each X_i's fleet within a certain area of interest (AOI) and period of interest (POI) were available through Larus clients
3. Adverse events were simulated as done in Scenario 1
4. Larus RMF provided a risk-aware view of situational elements (Level 2 Fusion) that affect each X_i's operational efficiency
5. Larus RMF provided the automatic generation of multiple candidate responses (from Y's perspective) to mitigate the risky events
   - reschedule ship loading/unloading operations
   - reallocate resources (cranes, fantoosies, etc.)
   - buying resources from other suppliers
   - etc.

Scenario 3 Definition

1. Multiple freight ship companies X_1, …, X_n, a port authority Y and a trucking company Z were selected for analysis
2. Real-time AIS feeds for all ships in each X_i's fleet within a certain area of interest (AOI) and period of interest (POI) werr available through Larus clients
3. Adverse events were simulated as done in Scenario 1
4. Larus RMF provided a risk-aware view of situational elements (Level 2 Fusion) that affect each X_i's operational efficiency
5. Larus RMF provided the automatic generation of multiple candidate responses (from Y's and Z's perspective) to mitigate the risky events
   - reschedule ship loading/unloading operations
   - reallocate resources (cranes, fantoosies, etc.)
   - buying resources from other suppliers
   - etc.

Publication List (1)

1. **Mining Port Congestion Indicators from Big AIS Data**, 2018 International Joint Conference on Neural Networks at Rio de Janeiro, Brazil, July 2018.
2. **Modeling the Speed-based Vessel Schedule Recovery Problem using Evolutionary Multiobjective Optimization**, June 2018 Information Sciences 448-449:53-74 DOI: 10.1016/j.ins.2018.03.013
3. **A Computational Model of Multi-scale Spatiotemporal Attention in Video**, DOI: 10.1007/978-3-319-93000-8_15, Image Analysis and Recognition, June 2018.
4. **Responding to Illegal, Unreported and Unregulated Fishing with Evolutionary Multi-Objective Optimization**, 2018 IEEE International Conference on Computational Intelligence & Virtual Environments for Measurement Systems and Applications (CIVEMSA 2018), Ottawa, Canada, June 2018

Publication List (2)

5. **Automatic Identification of Maritime Incidents from Unstructured Articles**, 2018 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA), Boston, USA, June 2018
6. **Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations**, April 2018, Conference: 31st Canadian Conference on Artificial Intelligence, Toronto, Canada, May 2018
7. **Big-Data-Enabled Modelling and Optimization of Granular Speed-based Vessel Schedule Recovery Problem**, December 2017, DOI: 10.1109/BigData.2017.8258122 Conference: 2017 IEEE International Conference on Big Data (IEEE BigData 2017), Boston, December 2017

Publication List (3)

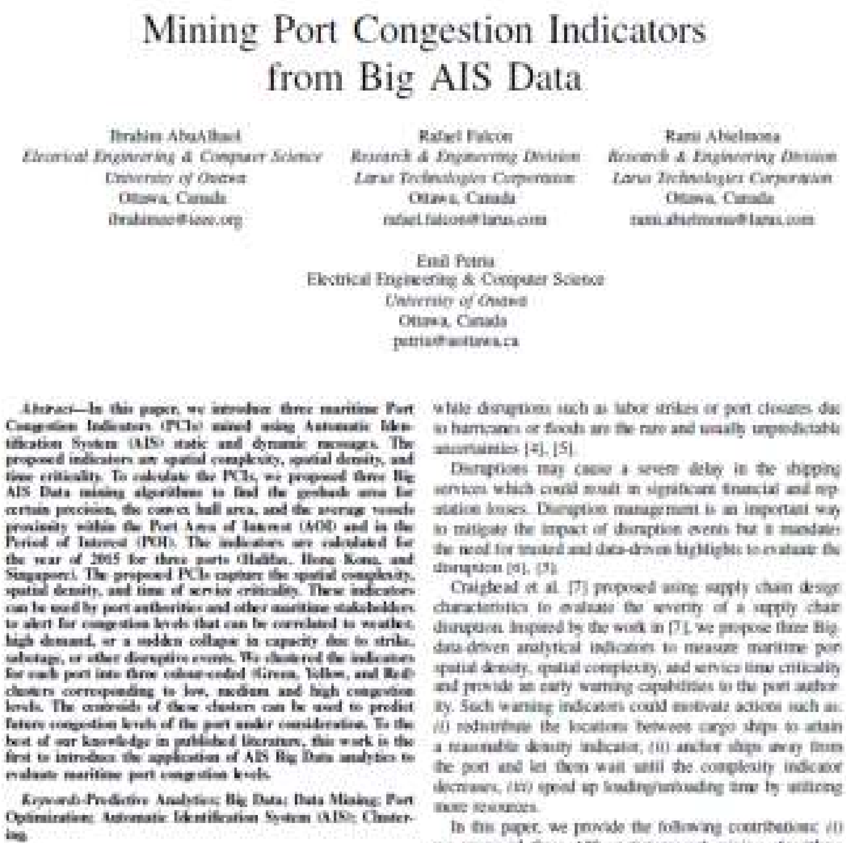
8. **A Reinforcement Learning Approach to Tackle Illegal, Unreported and Unregulated Fishing** , 2017 IEEE Symposium on Computational Intelligence for Security and Defense Applications (IEEE CISDA 2017) At: Hawaii, USA, November 2017

9. **Automating Maritime Risk Assessment with Genetic Fuzzy Systems**, 2nd International Symposium on Fuzzy and Rough Sets (ISFUROS), Varadero, Cuba, October 2017

10. **Extraction of Spatiotemporal Descriptors for Maritime Vessel Detection using Attentive Sensing**, British Machine Vision Conference (BMVC 2017) - 5th Activity Monitoring by Multiple Distributed Sensing (AMMDS) Workshop, London, UK, September 2017

11. **Continuous Risk-Aware Response Generation for Maritime Supply Chain Disruption Mitigation**, 2017 International Conference on Distributed Computing in Sensor Systems (DCOSS 2017), Ottawa, Canada, June 2017

1) Mining Port Congestion Indicators from Big AIS Data



Mining Port Congestion Indicators from Big AIS Data

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***Abstract*—In this paper, we introduce three maritime Port Congestion Indicators (PCIs) mined using Automatic Identification System (AIS) static and dynamic messages. The proposed indicators are spatial complexity, spatial density, and time criticality. To calculate the PCIs, we proposed three Big AIS Data mining algorithms to find the geohash area for certain precision, the convex hull area, and the average vessels proximity within the Port Area of Interest (AOI) and in the Period of Interest (POI). The indicators are calculated for the year of 2015 for three ports (Halifax, Hong Kong, and Singapore). The proposed PCIs capture the spatial complexity, spatial density, and time of service criticality. These indicators can be used by port authorities and other maritime stakeholders to alert for congestion levels that can be correlated to weather, high demand, or a sudden collapse in capacity due to strike, sabotage, or other disruptive events. We clustered the indicators for each port into three colour-coded (Green, Yellow, and Red) clusters corresponding to low, medium and high congestion levels. The centroids of these clusters can be used to predict future congestion levels of the port under consideration. To the best of our knowledge in published literature, this work is the first to introduce the application of AIS Big Data analytics to evaluate maritime port congestion levels.**

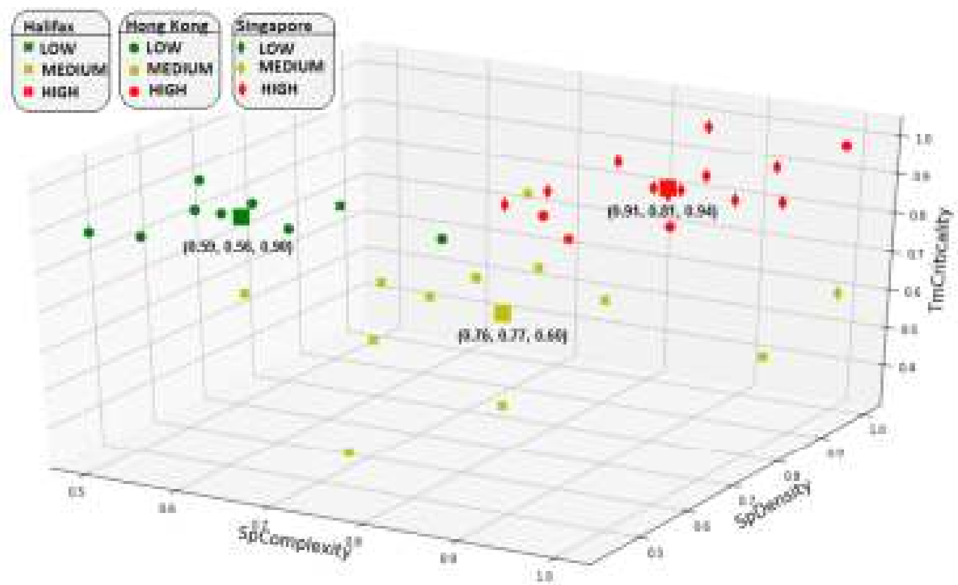
***Keywords*-Predictive Analytics; Big Data; Data Mining; Port Optimization; Automatic Identification System (AIS); Clustering**

while disruptions such as labor strikes or port closures due to hurricanes or floods are the rare and usually unpredictable uncertainties [4], [5].

Disruptions may cause a severe delay in the shipping services which could result in significant financial and reputation losses. Disruption management is an important way to mitigate the impact of disruption events but it mandates the need for trusted and data-driven highlights to evaluate the disruption [6], [7].

Craighead et al. [7] proposed using supply chain design characteristics to evaluate the severity of a supply chain disruption. Inspired by the work in [7], we propose three Big data-driven analytical indicators to measure maritime port spatial density, spatial complexity, and service time criticality and provide an early warning capabilities to the port authority. Such warning indicators could motivate actions such as: *(i)* redistribute the locations between cargo ships to attain a reasonable density indicator, *(ii)* anchor ships away from the port and let them wait until the complexity indicator decreases, *(iii)* speed up loading/unloading time by utilizing more resources.

In this paper, we provide the following contributions: *(i)* we proposed three AIS spatiotemporal mining algorithms



2) Modeling the Speed-based Vessel Schedule Recovery Problem using Evolutionary Multi objective Optimization

Modeling the Speed-based Vessel Schedule Recovery Problem using Evolutionary Multiobjective Optimization

Fatemeh Cheraghchi[b], Ibrahim Abualhaol[b], Rafael Falcon[a,b], Rami Abielmona[a,b], Bijan Raahemi[b], Emil Petriu[b]

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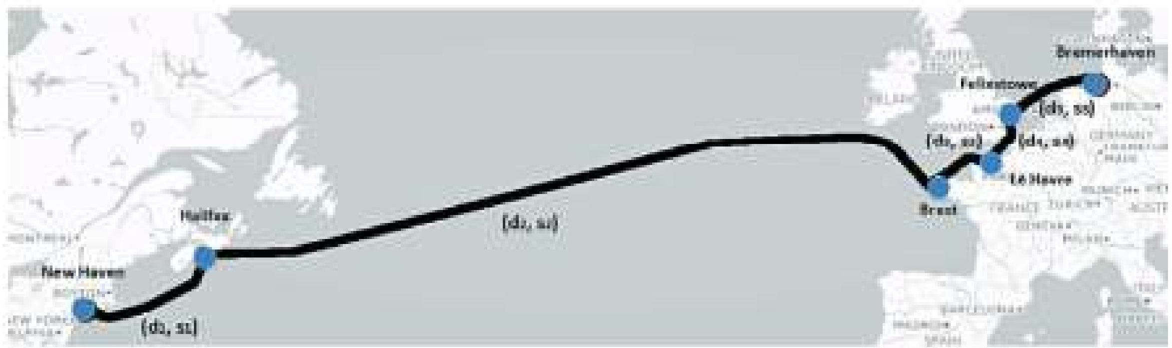
Abstract

Liner shipping is vulnerable to many disruptive factors such as port congestion or harsh weather, which could result to delay in arriving at the ports. It could result in both financial and reputation losses. The vessel schedule recovery problem (VSRP) is concerned with different possible actions to reduce the effect of disruption. In this work, we are concerned with speeding up strategy in VSRP, which is called the Speed-based Vessel Schedule Recovery Problem (S-VSRP). We model S-VSRP as a multiobjective optimization (MOO) problem and resort to several multiobjective evolutionary algorithms (MOEAs) to approximate the optimal Pareto set, which provides vessel route-based speed profiles. It gives the stakeholders the ability to tradeoff between two conflictive objectives: total delay and financial loss. We evaluate the problem in three scenarios (i.e., scalability analysis, vessel steaming policies, and voyage distance analysis) and statistically validate their performance significance. According to experiments, the problem complexity varies in different scenarios, and NSGAII performs better than other MOEAs in all scenarios.

Keywords: Multiobjective Optimization, Multiobjective Evolutionary Algorithms, Vessel Schedule Recovery Problem,



3) A Computational Model of Multi-scale Spatiotemporal Attention in Video Data

A Computational Model of Multi-Scale Spatiotemporal Attention in Video Data

Roman Palenichka[1], Rafael Falcon[1,2], Rami Abielmona[1,2], Emil Petriu[1]

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Abstract. This paper describes a spatiotemporal saliency-based attention model in applications for the rapid and robust detection of objects of interest in video data. It is based on the analysis of feature-point areas, which correspond to the object-relevant focus-of-attention (FoA) points extracted by the proposed multi-scale spatiotemporal operator. The operator design is inspired by three cognitive properties of the human visual system: detection of spatial saliency, perceptual feature grouping, and motion detection. The model includes attentive learning mechanisms for object representation in the form of feature-point descriptor sets. The preliminary test results of attention focusing for the detection of feature-point areas have confirmed the advantage of the proposed computational model in terms of its robustness and localization accuracy over similar existing detectors.

Keywords: spatiotemporal attention, video data, attention operator, local scale, object detection, spatial saliency, property coherence, temporal change.

4) Responding to Illegal, Unreported and Unregulated Fishing with Evolutionary Multi-Objective Optimization

Responding to Illegal, Unreported and Unregulated Fishing with Evolutionary Multi-Objective Optimization

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***Abstract*—Illegal, unreported and unregulated (IUU) fishing is largely responsible for dwindling fish stocks and marine habitat destruction. It is estimated that IUU fishing accounts for about 30% of all fishing activity worldwide, both on open oceans and within national exclusive economic zones. Responding to IUU fishing incidents is of paramount importance to law enforcement and marine environment protection organizations. This paper employs Evolutionary Multi-Objective Optimization (EMOO) to automatically generate a set of promising candidate responses once an IUU fishing event has been identified. Four EMOO algorithms will explore the trade-off among three conflicting decision objectives, namely (1) the proximity to the target (IUU fishing vessel), (2) the total cost of the response for all engaged assets and (3) the probability of confirming the detection of the offending vessel inside the fishing zone, which is important for**

marine environment protection organizations in their pursuit of effective MDA [4].

Responding to an IUU event is quite challenging, especially because the offending fishing vessel would have to be caught in the act (or at least inside a forbidden fishing zone) so as to establish legal grounds for prosecution. To this end, we have modeled the response to IUU events as a multi-objective numerical optimization problem and solved it through several Evolutionary Multi-Objective Optimization (EMOO) algorithms. In other words, we employ EMOO methods to automatically generate a set of promising candidate responses once an IUU fishing event has been properly identified. Four

5) Automatic Identification of Maritime Incidents from Unstructured Articles

Automatic Identification of Maritime Incidents from Unstructured Articles

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***Abstract*—In this paper, we present two Natural Language Processing (NLP) techniques for identifying maritime incidents described in unstructured articles from multiple sources. The first technique is a document classification scheme that determines if an article describes a maritime incident. Two variations of each article are created: the first only contains the article's title, the other contains the title and content. These are converted to both binary and frequency bag-of-words. Furthermore, two feature selection methods are tested: Weka's *CfsSubsetEval* and retaining the 300 most frequent words. Each dataset is tested with 41 classifiers from the Weka suite, with the most accurate classifiers including Logistic Regression (98.5%), AdaBoostM1(BayesNet) (98.33%), and RandomForest (97.56%). The second technique performs information extraction on an article to determine the location of the maritime incident. In addition to using regular expressions and Named Entity Recognition (NER), the approach focuses its attention on sentences that contain piracy keywords as well as sentences which occur earlier in the article. In our testing, this approach achieved 87.9% accuracy. Together the two techniques form a pipeline where the positive examples from the document classification algorithm are fed into the information extraction algorithm.**

throughout the week. Both of these textual sources have been recently used to synthesize a risk-aware picture of the maritime environment together with other structured, sensor-emitted data sources such as Automatic Identification System (AIS) [3].

In this work, we attempt to exploit an additional type of data source: articles from maritime magazines such as *The Maritime Executive*[3], *gCaptain*[4], *World Maritime News*[5], *Marine Log*[6], *Marine Link*[7], non-maritime newspapers such as *The New York Times*[8], as well as unstructured reports from the *Regional Cooperation Agreement on Combating Piracy and Armed Robbery against Ships in Asia (ReCAAP)*[9]. Unlike IMB, NGA, and ReCAAP reports which are dedicated to describing maritime incidents, most magazine articles discuss the economics, politics, and news of the maritime world; only a small subset of these describe maritime incidents. Additionally, the magazine articles are unstructured, which makes it more difficult to automatically extract the details of the incident. Finally, the articles may lack specific details about

ACCURACY BY DATA SOURCE

	Classification Accuracy	get_location Accuracy
The Maritime Executive	93.44%	86.89%
gCaptain	97.53%	92.59%
ReCAAP	–	95.65%
World Maritime News	97.56%	75.61%
The New York Times	96.42%	85.71%
Marine Log	98.24%	91.12%
Marine Link	100%	77.78%

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6) Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations

Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations

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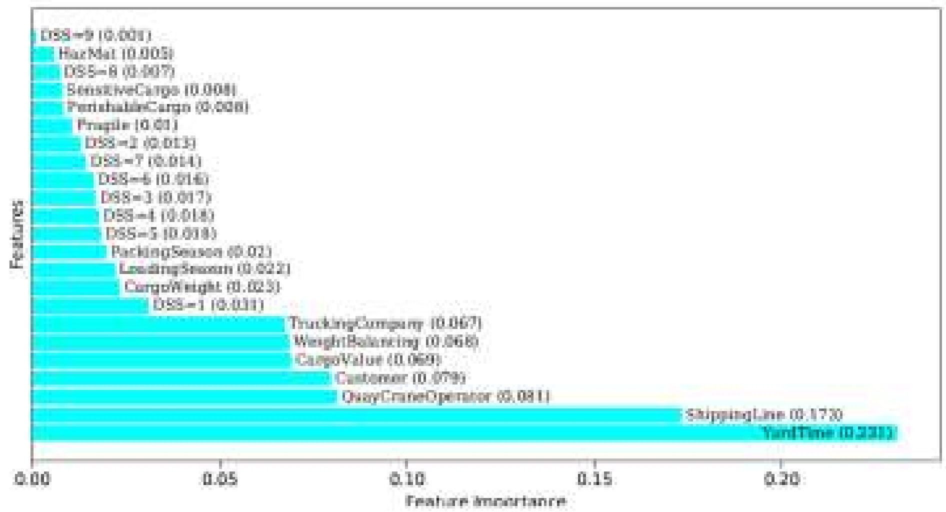
Abstract. A company operating in a commercial maritime port often experiences clients filing insurance claims on damaged shipping containers. In this work, multiple classifiers have been trained on synthesized data, to predict such insurance claims. The results show that Random Forests outperform other classifiers on typical machine learning metrics. Further, insights into the importance of various features in this prediction are discussed, and their deviation from expert opinions. This information facilitates selective information collation to predict container claims, and to rank data sources by relevance. To our knowledge, this is the first publication to investigate the factors associated with container damage and claims, as opposed to ship damage or other related problems.



7) Big-Data-Enabled Modelling and Optimization of Granular Speed-based Vessel Schedule Recovery Problem

Big-Data-Enabled Modelling and Optimization of Granular Speed-based Vessel Schedule Recovery Problem

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Abstract—The Automatic Identification System (AIS) is a vessel tracking system that automatically provides updates on a vessel's movement and other relevant voyage data to vessel traffic management centres and operators. Aside from assisting in real-time tracking and monitoring marine traffic, this system is used in the analysis of historical navigation patterns. In this work, we mined and aggregated vessel speeds from AIS messages within geohashed regions at different precision levels. This granulated, real-world information was brought into the formulation of a Speed-based Vessel Schedule Recovery Problem (S-VSRP). The goal is to mitigate disruptions in vessel schedule by adjusting the speeds while also conforming to the historical navigation patterns reflected in the AIS data. We introduce a new model for vessel schedule speed recovery problem by formulating it as a multi-objective optimization (MOO) problem called the Big-Data-enabled Granular S-VSRP (G-S-VSRP) and propose meta-heuristic optimization methods to find Pareto-optimal solutions. The three objectives are: (1) minimizing the total delay between origin and destination ports, (2) minimizing total financial loss, and (3) maximizing the average speed compliance with historical speed limits. Three evolutionary multi-objective optimizers (EMOO) were investigated and utilized to approximate the Pareto-optimal solutions providing vessel voyage speeds. The Pareto front gives the ability to inspect the tradeoff among the three conflicting objectives. To the best of our knowledge, this is the first time historical AIS data has been exploited in the published literature to mitigate disruptions in vessel schedules.

Keywords—Geohashed speed mining; Evolutionary algorithm; Multi-objective optimization; Disruption Management; Vessel Schedule Recovery Problem; Meta-heuristic; Automatic Identification System (AIS).

unexpected wait time for port access occur frequently and can be managed by probabilistically modeling the degree of uncertainty [2], while disruptions such as labor strikes or port closures due to hurricanes or floods are the rare and usually unpredictable uncertainties [3] [4]. Disruptions may cause a severe delay in the shipping services which could result in significant financial and reputation losses. To manage the disruption and mitigate the delay impact, dynamically recovering from disruption events is suggested [4]. In the disruption management, finding a recovery plan is called a solution for the Vessel Schedule Recovery Problem (VSRP). The solution considers four possible actions, or a combination thereof to manage the disruption's consequences [3] [5]. These actions perform recovering by speeding up, swapping the visitation order of the ports in the voyage, skipping the ports along the voyage, or accepting the delay and taking no action.

The Automatic Identication System (AIS) is a vessel tracking system that automatically provides updates on a vessel's movement and other relevant ship voyage data to other parties. Each ship equipped with an AIS transponder sends out a packet every few seconds. Dynamic data that is transmitted include position, speed, course, true heading and rate of turn. Less frequent messages transmit ship static data, draught, and other voyage-related information [6].

With the ever-increasing capability of collecting abundant data from a plethora of sources, according to Ericsson [7],

8) A Reinforcement Learning Approach to Tackle Illegal, Unreported and Unregulated Fishing

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Abstract—Illegal, unreported and unregulated fishing is a worldwide problem that is causing local and global financial losses, depleting natural resources, changing our diverse ecosystem and causing undue pressure upon the fishing industry. This paper presents a Reinforcement-Learning-based approach to response generation once this type of fishing event has been detected. The Fuzzy Actor Critic Learning technique is used to train one or more pursuers to effectively catch an evader. This technique is utilized on both the pursuer and evader vessel agents in order to simulate real-world illegal and unreported fishing pursuit events. Simulations are executed along two such scenarios, namely the Automatic Identification System Gaps and the Local Fishing, Foreign Delivery ones involving both illegal and unreported fishing vessels (as evaders) and law enforcement vessels (as pursuers). Experimental results are presented and analyzed whereby the pursuers catch the evading fishing vessels within a preset capture time. To our knowledge, this is the first time any Reinforcement Learning techniques have been applied as a response to such fishing events. The proposed methodology here is generic enough that it can be easily extrapolated to other domains.

According to the Food and Agriculture Organization (FAO)'s Fisheries and Aquatic Department's 2016 world report, the financial losses caused by IUU fishing are up to $25 billion per year [3]. Domestically, illegal fishing operations have negative economic impacts such as financial losses to legal local fishermen, Gross National Product (GNP) loss to the economy, reduction in future productivity and biodiversity of the marine ecosystem, increased pressure on endangered species and so on [3]. Two types of illegal fishing scenarios discussed in the paper include: *Automatic Identification System (AIS) Gaps* and *Local Fishing, Foreign Delivery* (LFFD).

The AIS gaps scenario describes a situation where vessels "go dark" (i.e., intentionally turn off their AIS transponder) for significant regular intervals in order to stop reporting their geographical position, especially near fishing zone borders and sensitive areas which could indicate that these vessels are trying to fish in zones for which they do not have permission. The LFFD scenario is concerned with a situation where a

9) Automating Maritime Risk Assessment with Genetic Fuzzy Systems

Automating Maritime Risk Assessment with Genetic Fuzzy Systems

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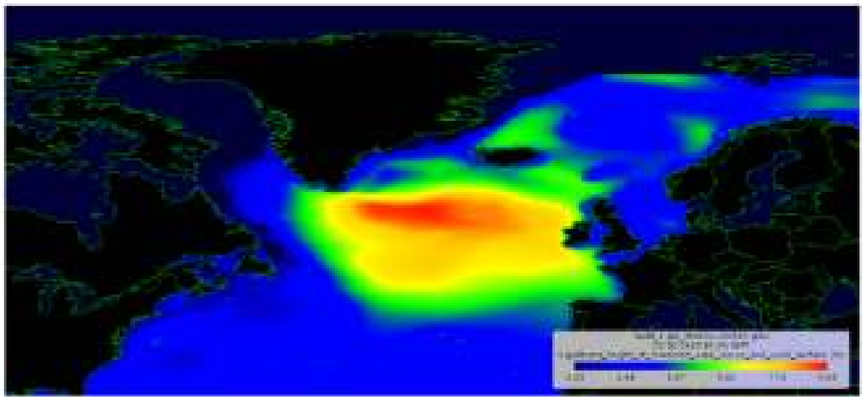
Abstract. Assessing the overall risk of maritime entities over time is a pivotal issue in Maritime Risk Assessment (MRA). This process largely hinges on human expertise to characterize the risk features of interest as well as their mathematical underpinnings and the way in which their local risk outputs are amalgamated to produce an overall risk value. In this paper, we take steps towards automating this time-consuming endeavour by learning the fuzzy rule base (FRB) governing the Risk Assessment module of an existing Risk Management Framework (RMF) directly from data. We employ several genetic fuzzy systems (GFSs) available in KEEL to optimize the membership functions and learn the structure of a FRB used for risk assessment purposes. The proposed methodology is illustrated with two case studies in maritime surveillance. The empirical results indicate that the New Slave (NSLV) algorithm generated the most accurate FRBs, while the Hybrid Genetics-Based Machine Learning (GBML) algorithm generated the most interpretable FRBs. To the best of our knowledge, this is the first attempt to apply GFSs in MRA.

Keywords: Maritime Domain Awareness; Risk Management; Genetic Algorithms; Fuzzy Systems; Multi-Objective Optimization



10) Extraction of Spatiotemporal Descriptors for Maritime Vessel Detection using Attentive Sensing

Extraction of Spatiotemporal Descriptors for Maritime Vessel Detection using Attentive Sensing

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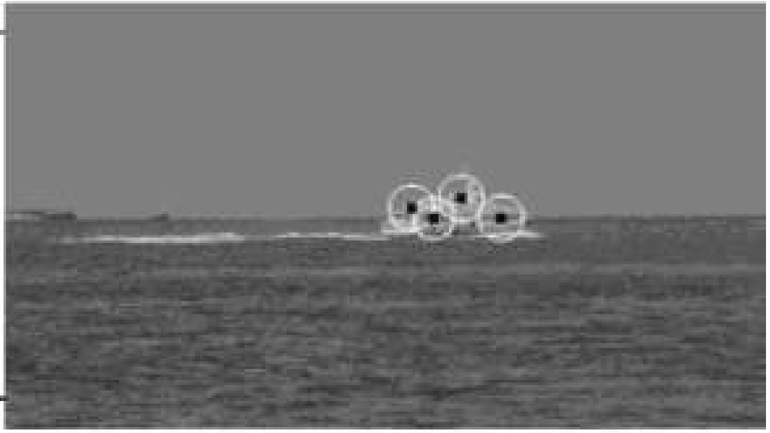
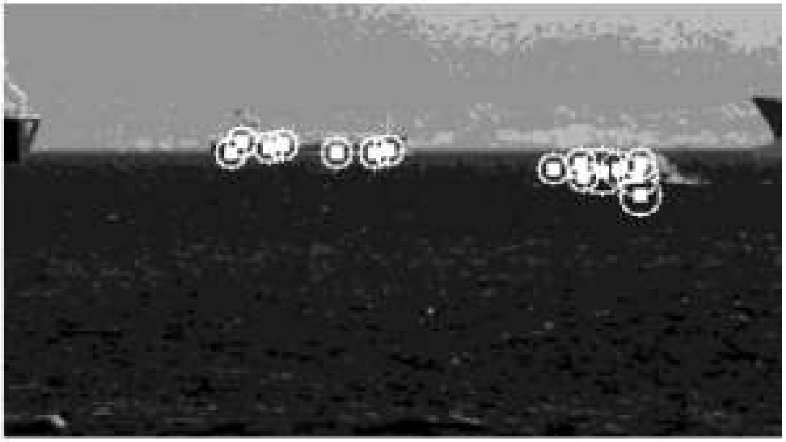


Abstract

This paper is dedicated to the robust extraction of image features and descriptors for subsequent ship detection in maritime videos. The attentive sensing approach is adopted for the descriptor-based ship detection using object-relevant feature point areas. They are robustly extracted as salient maxima locations of the proposed attention operator. Spatiotemporal descriptors are estimated in the feature point areas in the form of corresponding local descriptor vectors. Different types of descriptor components such as pose, planar shape, intensity and temporal change are normalized and combined into a local descriptor vector. A novel descriptive entity called spatiotemporal feature-saliency pattern (SFSP) is proposed to transformation-invariantly aggregate several descriptor vectors into a single set of feature-point descriptors. Object or event detection effectively proceeds through matching of current SFSPs with the reference ones obtained by clustering-based machine learning procedures. Preliminary test results have confirmed the performance advantage of the proposed SFSP-based method over existing descriptor extraction algorithms for maritime vessel detection.



11) Continuous Risk-Aware Response Generation for Maritime Supply Chain Disruption Mitigation

Continuous Risk-Aware Response Generation for Maritime Supply Chain Disruption Mitigation

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Abstract—Supply chains in the current world often stretch across the globe, requiring extensive use of transportation modes. As they become increasingly crucial, a greater focus is put on streamlining their operation to reduce waste. The combination of these two realities make supply chains particularly vulnerable to disruptions that have profound effects on downstream actors.

Much information is needed is needed to predict and mitigate disruptions. The Internet of Things (IoT) is a new paradigm that integrates the sensing and actuation capabilities of the involved actors into an interconnected web. A maritime IoT (mIoT) could be leveraged to gather the necessary data within the maritime domain to predict these disruptions and to suggest possible mitigation actions.

In this paper, we put forth a methodology to detect potentially disruptive events in a maritime supply chain (MSC) and generate candidate mitigating responses. The proposed framework places risk as the cornerstone of the data-driven analysis and uses a multi-criteria decision approach to propose appropriate actions.

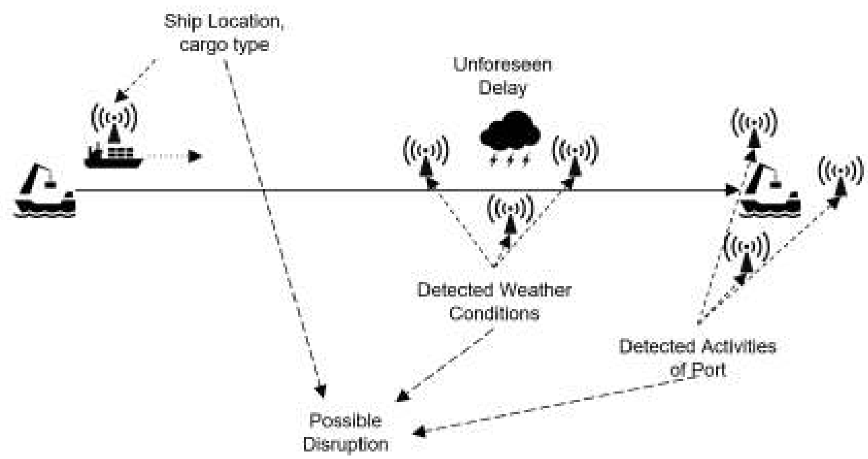
An application of the system to predict and mitigate a disruption in a maritime segment of a supply chain is studied. Solutions are composed of combinations of actions that can be applicable in a real context. This system is validated through a scenario in which a weather event causes a disruption in maritime transportation destined to fulfill a supply contract. Finally, conclusions on the system are provided.

gathering capabilities of the so called *maritime IoT* (mIoT), the risk of a disruption could be predicted and/or tracked [5], while actions could be taken to mitigate it.

This paper attempts to mitigate supply chain disruptions through a combination of risk-aware analysis and multi-criteria decision making. The proposed methodology leans on two fundamental building blocks: (1) a reactive Risk Management Framework (RMF) and (2) a continuous multi-objective optimization (MOO) process. A synthetic scenario and simulation with the ensuing detailed analysis is also presented to validate the proposed methodology.

First, the reactive design of a previously introduced RMF [6] that has been adapted to the IoT paradigm is exploited. The RMF is able to integrate incoming information as soon as it is received into a risk-driven analysis that allows mitigation actions to quickly adapt to the ever changing environment. Additionally, the multi-modular RMF architecture allows a set of dynamic data sources to be added and removed on demand, thus reflecting the realities of the mIoT.

Second, an optimization technique to generate potential mitigation solutions is presented. These solutions are combi-



12) Data-Driven Vessel Service Time Forecasting using Long Short-Term Memory Recurrent Neural Networks

Data-Driven Vessel Service Time Forecasting using Long Short-Term Memory Recurrent Neural Networks

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***Abstract*—In this paper, we provide a proof of concept on how to model and forecast average Vessel Service Time ($\overline{VST}$) using Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs). The proposed model is learned from the Automatic Identification System (AIS) data by using machine learning. Geohash area ($GeoArea$) with a certain precision, convex hull area ($ConvArea$), and average vessel proximity (Δ) are mined for the port of Singapore every hour. These three metrics are used to calculate port spatial complexity ($SpComplexity$) and port spatial density ($SpDensity$) indicators. In addition, we propose an algorithm to mine the $\overline{VST}$ and associate that with the mined $GeoArea$, $ConvArea$, and Δ and the calculated indicators (i.e., $SpDensity$ and $SpComplexity$). Then, an LSTM model is trained and subsequently tested to forecast future $\overline{VST}$, as Port Authorities are increasingly relying on data-driven insights for decision-making purposes. We trained and tested several LSTM models with four different time aggregation granularities (2, 4, 8, and 12 hours) and provided performance comparisons between them in terms of Mean Square Error (MSE). The experiments emphasized the feasibility of the proposed model to forecast $\overline{VST}$.**

***Keywords*-Long Short-Term Memory (LSTM); Automatic Identification System (AIS); Port Indicators; Vessel Service Time; Geohash; Convex Hull; Forecasting.**

analytics to evaluate the disruption [5].

Two recent data-driven approaches to optimize maritime operations can be found in [6], and [7]. The former makes use of historical vessel speed profiles to mitigate vessel delays while the latter models port congestion indicators by means of several metrics mined from AIS data. These indicators motivate actions such as: *(a)* redistribute cargo vessel locations to attain a reasonable density indicator, *(b)* anchor vessels away from the port and have them wait until the complexity indicator decreases, *(c)* speed up loading/unloading time by utilizing more resources.

Building on our work in [7], in this paper we provide the following novelties: *(i)* we propose an AIS-based mining algorithm to estimate $\overline{VST}$ and associate that with: port spatial complexity $SpComplexity$, port spatial density ($SpDensity$), convex hull area ($ConvArea$), geohash area ($GeoArea$), and average vessel proximity (Δ). Then, *(ii)* we architect a simple Long-Short Term Memory (LSTM) Recurrent Neural Network (RNN) to model and forecast future $\overline{VST}$. Finally, *(iii)* we investigate the effect of time aggregation granularity on the accuracy of the proposed models. Mining and predicting average $\overline{VST}$ from data will

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