Optimizing Shipping Container Damage Prediction and Maritime Vessel Service Time in Commercial Maritime Ports through High Level Information Fusion

A Thesis submitted in Partial Fulfillment of the Requirements for the Doctorate in Philosophy in Computer Science

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Abstract

The overwhelming majority of global trade is executed over maritime infrastructure, and port-side optimization problems are significant given that commercial maritime ports are hubs at which sea trade routes and land/rail trade routes converge. Therefore, optimizing maritime operations brings the promise of improvements with global impact. Major performance bottlenecks in maritime trade process include the handling of insurance claims on shipping containers and vessel service time at port. The former has high input dimensionality and includes data pertaining to environmental and human attributes, as well as operational attributes such as the weight balance of a shipping container; and therefore lends itself to multiple classification methodologies, many of which are explored in this work. In order to compare their performance, a first-of-its-kind dataset was developed with carefully curated attributes. The performance of these methodologies was improved by exploring metalearning techniques to improve the collective performance of a subset of these classifiers. The latter problem formulated as a schedule optimization, solved with a fuzzy system to control port-side resource deployment; whose parameters are optimized by a multi-objective evolutionary algorithm which outperforms current industry practice (as mined from real-world data). This methodology has been applied to multiple ports across the globe to demonstrate its generalizability, and improves upon current industry practice even with synthetically increased vessel traffic.

Acknowledgments

It takes a village... and mine was possibly the best. My mentors and supervisors always stood by my side, never giving up on me. Panch Mama, Dr. Emil Petriu, Dr. Rami Abielmona, and Dr. Rafael Falcon always offered me the guidance I needed. Meanwhile, Wayne Smith and Montreal Terminal Gateway Partnerships provided much needed insights from the industry, without which I would have been unable to formulate the problems I worked on, much less the solutions I designed and discussed with Alyssa Wai-Yi Fred Wong. I would be remiss if I didn't thank Tapan Oza for continuing to help draw my graphs the night before a submission deadline. I've always found it interesting how my friendships evolve over time, and none offers more pause for reflection than that I now get to call Phil Dr. Curtis and thank him for all the professional support through seemingly impossible challenges; speaking of which, I must thank Alex Teske, Patrick Santos and Jonathan Ermel for the overwhelming amounts of help with various code snippets and databases for my experiments.

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Nomenclature

AIS Automated Identification System

AOI Area of Interest

ATA Actual Time of Arrival

ATD Actual Time of Departure

AUC Area Under the Curve

BAP Berth Allocation Problem

CART Classification and Regression Tree

CI Computational Intelligence

DFIG Data Fusion Information Group

DSS Douglas Sea Scale

EOI Event of Interest

ETA Estimated Time of Arrival

ETD Estimated Time of Departure

GA Genetic Algorithm

GPS Global Positioning System

HLIF High Level Information Fusion

IMO International Maritime Organization

JDL Joint Directors of Laboratories

KNN k-Nearest Neighbors

LLIF Low Level Information System

LOBO Leave One Batch Out

MIP Mixed Integer Programming

ML Machine Learning

MMSI Maritime Mobile Service Identity

MOE Measure of Effectiveness

MOEA Multi-objective Evolutionary Algorithm

MOP Measure of Performance

NN Neural Network

NOAA National Oceanographic and Atmospheric Administration

POI Period of Interest

RANSAC Random Sample Consensus

ROAR Random Online Aggressive Racing

SAW Situational Awareness

SMAC Sequential Model-based Optimization for General Algorithm Configuration

SOSCIP Southern Ontario Smart Computing for Innovation Platform

STDF State Transition Data Fusion

SVM Support Vector Machine

TEU Twenty-foot equivalent Unit

1. Introduction

The overwhelming majority of global trade is conducted over maritime infrastructure, implying that improvements in the efficiency of maritime operations improve global trade efficiency. Specifically, commercial maritime ports are large and complex hubs where marine traffic and land and rail traffic converge, connecting global trade to local infrastructure. Thus, optimizing operations in commercial maritime ports is the first front at which such optimization efforts would be maximally effective.

Commercial maritime ports face many challenges in the optimization of their internal processes. Broadly, these processes can be classified into the following two types:

1. processes that interrupt regular port operations, which must be minimized in order to minimize interruptions to regular port operations
2. regular port operations, in order to optimize process efficiency

One frequently occurring process that interrupts regular port operations is the workflow induced by the filing of an insurance claim on a damaged shipping container (independently of its contents, which may also be damaged; however, that problem is out of the scope of the current work). This induces extensive review by port-side personnel in an investigation of the various operations that may have caused the container to sustain damage. Automating the prediction of such damage and identifying the potential cause thereof is therefore an avenue of improvement, which would minimize the interruptions this process would cause to regular port operations. This problem is discussed in more detail in Sec. 1.1.1.

On the other hand, a process at the core of commercial maritime port operations is the loading and unloading of shipping containers from cargo vessels. Central to this process are the quay cranes (and their respective operators) that physically move the containers between the vessel and port. Optimizing the number of quay cranes deployed at any one time would therefore optimize the process of moving shipping containers between a vessel and the port, thus minimizing the total time required to service any given vessel at its berth. Minimizing vessel service time by increasing the deployment of port-side personnel and resources comes at the increased operational cost of these resources and personnel (in the form of wages). Therefore, this optimization must account for both of these optimization parameters, to identify a solution that strikes an acceptable balance between the two. This problem is discussed in more detail in Sec. 1.1.3.

1.1. Problem Definition

Optimizing maritime port operations can be broken down into the two primary problems, namely predicting shipping container damage and optimizing maritime vessel service time. Advances made in the former problem alleviate the interruptions caused to the otherwise regular flow of commercial maritime port operations, which in turn reduces disruptions to the efficiency at which the port operates. On the other hand, advances made in the latter problem improve the operational efficiency of commercial maritime ports, which in turn improves their throughput and operational capacity, increasing the global capacity for maritime trade. These problems are specified more formally in this section.

1.1.1. Predicting Shipping Container Damage

Predicting shipping container damage can help alleviate port-side operational bottlenecks, by narrowing the scope of shipping container whose data must be analyzed (and the breadth of the relevant analysis as well). In order to do so, data is collected on the features of the shipping container, pertaining to

- cargo value
- presence of hazardous cargo in the container
- cargo longevity
- cargo sensitivity
- mass distribution of cargo in the shipping container
- amount of time spent in the storage yard
- exposure to rough seas along voyage from source to destination ports
- exposure to calm seas along voyage from source to destination ports
- container packing season
- container loading season
- cargo fragility
- quay crane operator

Given this data, classifiers may be trained to predict which shipping containers may be damaged and therefore filed claims upon (as a binary classification problem). Doing so allows for automating the collation and analysis of the relevant data in order to determine the most likely point of damage for the Insurance Claims Coordinator to analyze in a more targeted manner, thereby streamlining this process. This is further explained in Sec. 2.6.1.

1.1.2. Improving Shipping Container Claims Prediction with Metalearning

While the problems discussed thus far pertain to the optimization of port-side operations, they optimize these operations on a per-instance basis - insights gained from previous runs of the optimization are lost and are not used in future optimization efforts. Thus, training a model to on historical performance data will allow for the optimization of algorithm selection and algorithm parameter selection for the handling of a new unseen data record by discovering correlations between data meta-features and the performance of the trained classifiers. These correlations allow for the intelligent combining of the outputs of multiple classifiers in order to improve the overall classification accuracy. The exact methodologies used for this are explored in detail in Sec. 3.5.

1.1.3. Dynamic Allocation of Port-side Resources to Optimize Vessel Service Time

While predicting shipping container damage does indeed alleviate operational bottlenecks, port-side operations can be further streamlined by reducing the probability of port-side shipping container damage. Since this may be caused by increased operational speed (as opposed to increasing operational throughput without increasing speed at which various operational components function), While guidelines on operational speed are known [6], operational throughput can be improved by optimizing the deployment of port-side resources. The deployment of resources is performed by means of adapting the number of quay cranes used to service an incoming vessel, while the congestion of maritime vessels in a port's waters is used as a performance measure to guide the optimization. This is therefore a proactively adaptive resource deployment problem as explained in Sec. 2.6.2.

1.2. Motivation

Commercial Maritime Ports are significant hubs of commerce to any national economy and account for over $250M per month in Canada [7]. These ports are typically partitioned into terminals, within which shipping companies may load and discharge ships with cargo. Therefore, commercial operations within these terminals are of significant importance and improving their efficiency, efficacy, and throughput is of paramount concern, second only to various safety factors including safety to human life, infrastructure, and equipment. Improving internal processes within commercial maritime ports therefore help improve global economies, quality of living, and human and material safety.

A commercial maritime terminal faces challenges pertaining to:

- vessel arrival and departure schedules
- weather at port and at sea, as relating to the safety of cargo and personnel
- shipping container loading, unloading, storage and transportation, both within the port, and on board a shipping vessel while at sea
- the proper storage of shipping containers in order to expedite the process of loading and/or discharging a vessel, and to minimize risk exposure
- the deployment of equipment and personnel to increase throughput at minimal operating cost

Given these challenges, two optimization problems are identified and presented here (and will be explored in further detail throughout this thesis).

Predicting Shipping Container Damage An important aspect of port operational efficacy pertains to the safety and integrity of the cargo moving through the port's terminals. Such damage claims typically come with a large cost to companies operating at such ports. Not only does the settling of a claim have an associated financial cost, the investigation into the handling of the claim involves a complex decision making process, including identifying the various operators that handled the cargo, both internal and external to the port (from event logs, and surveillance data, and operational environment data). Fusing information from various sources (including ship voyage tracks, weather data, sea state data, commercial value of the cargo, vessel operator data, port side operator data, etc) helps construct a comprehensive understanding of the adversities faced by the ship, the shipping containers thereupon, and the cargo therein, to compute a profile of when and where any damages were incurred. As a result of such data fusion, it becomes feasible to compute a meaningful risk metric at each point along the life cycle of a shipping container, allowing for the automation within a decision support system to assist Bruce in the investigation of damage claims so that he can focus his efforts more on analyzing the already-collated data, rather than on meticulously collating it in the first place. This is further explored in Sec. 3.3.

Scheduling Quay Cranes to Improve Vessel Throughput In addition to workflows induced by claims on damaged shipping containers, ports are also concerned with increasing vessel service throughput. While this can be achieved by expanding infrastructure, doing so comes at a large capital cost [8]. On the other hand, intelligently deploying personnel and resources achieves the same goals of improving throughput without any additional capital costs, but with increased operational costs and related incidental costs. Doing so in a meaningful manner requires not only adequate reaction to current vessel servicing demand, but also accurate prediction of future demands on the port's resources to proactively respond to foreseeable demands. This is further explored in Sec. 4.4.

1.3. Use Case

Vessels arrive and leave the fictional maritime Port of Miranda (PoM) as part of the normal course of operations. Sometimes, the Insurance and Claims Coordinator (suppose his name is Bruce) receives an email from a customer about filing a claim on a damaged shipping container. Bruce must then review various personnel logs and surveillance footage to determine whether the damage occurred within PoM and whether the claim should therefore be disputed or settled. Predicting whether Bruce will receive a claim for a given shipping container will therefore allow for automated data collection for that container. Additionally, it allows for the automated prediction of the location of damage, so that Bruce is presented with a prioritized verification list to determine the point of damage.

While container damage prediction alleviates bottlenecks in the Insurance and Claims Coordinator's daily workflow, PoM's throughput is affected by the Quay Crane Deployment Problem (QCDP) [9, 10]. Rushing to increase the container handling throughput of these cranes does cause shipping container damage, which can therefore be alleviated by adjusting the number of cranes currently deployed to serve a given vessel. Allocating sufficient infrastructural and human resources to service such vessels allows for the timely and effective servicing of these vessels, reducing their exposure to risk of damage from port-side sources. This would further alleviate Bruce's workload, while improving the personnel scheduling on the port side as well.

1.4. Thesis Contribution

The contributions of this thesis are discussed in this section.

1.4.1. Predicting Insurance Claims on Shipping Containers

In order to alleviate operational bottlenecks caused by the filing of insurance claims on damaged shipping containers, many CI algorithms were used to determine the relationship between various features pertaining to a shipping container and whether it was damaged and ultimately claimed. In order to determine which features are indeed relevant to this study, a survey was created to capture this knowledge held by Canadian domain experts (see Sec. 3.1.4). This work is extended with metalearning (see Sec. 1.4.3) to explore the dynamic fusion the outputs of multiple classifiers to improve classification accuracy.

Given that this thesis (and publications arising therefrom) were the first in the literature to study this problem, the incremental contribution of this optimization is the most significant contribution to the existing body work.

1.4.2. Dynamic Allocation of Port-side Resources to Optimize Vessel Service Time

In order to further optimize port processes to reduce vessel service time and therefore improve throughput, port-side resources (personnel, equipment, and infrastructure) may be proactively deployed. This requires knowledge of vessel inbound and outbound schedules, which are known to ports. Since the primary point of contact between a vessel and port (with respect to loading and discharging cargo) is the quay crane at the berth, the primary optimization parameter pertains to the deployment of equipment and personnel to operate the quay cranes. Deploying equipment and personnel to service vessels in a timely manner also reduces the pressure on the terminal to hurriedly complete vessel service on time. Since increasing container handling speed causes increased risk to container damage [6], maintaining the timeliness of vessel service by increasing resource deployment reduces operational risk, which reduces the probability that a shipping container will sustain damage, which in turn reduces the number of claims sent to Bruce.

This is further explored in Sec. 4.4.

1.4.3. Improving Shipping Container Claims Prediction with Metalearning

The application of CI methodologies to maritime process optimization is not novel in and of itself. Additionally, the breadth of available CI methodologies highlights the role of nuance in the selection of an optimal algorithm to solve a given problem. This creates an opportunity to apply CI methodologies to determine the best CI technique to use for a given problem. This idea is currently being applied to the CI methodologies to select between CI methodologies used in predicting shipping container claims, and is further discussed in Sec. 1.4.3.1.

In order to address this, experiments are run to determine the correlations between artifacts of the values of features in a dataset (i.e. meta-features) and the best classifier or predictor to use given those meta-features. The correlations between classifier MOPs and the values of meta-features therefore determines the optimal classifier selection on new, unseen data. Experiments will also be run to discover correlations between classifier MOEs and data sources in order to guide optimal data source selection on new, unseen data. These are explored further with an example in Sec. 4.3.

The overarching idea is that rather than asking a single classifier for the claims classification of a single shipping container, Bruce would query a meta-learner to identify the best classifier to predict the claims classification of that shipping container. He would then ask that classifier to perform the prediction, based on which he make his decisions.

1.4.3.1. Dynamic Algorithm Selection through Metalearning

Within the context of this thesis, algorithms can be dynamically selected, specifically for data processing. These algorithms refer to process incoming data in Levels 1 and 2 of the DFIG Data Fusion model, and the threat and impact assessment algorithms in Level 3, including:

1. signals processing algorithms in Level 0
2. sub-object and object recognition algorithms in Level 1
3. situation assessment algorithms in Level 2
4. threat and impact assessment algorithms in Level 3

All of these algorithms can be evaluated for their efficiency (in terms of the amount of computational effort spent in executing the algorithm), and the accuracy (in terms of the difference between the computed value and the actual value) and efficacy (in terms of the relevance of the value computed by the algorithm to the objective) of their outputs. Therefore, a trust/veracity metric can be established for each algorithm, based on their historic performance.

1.4.3.2. Dynamic Datasource Selection

Within the context of this thesis, data sources are evaluated for the quality of the solutions they yield. For example, given two datasources (namely S_1 and S_2), the same methodology is used to train a model with data from either source (namely, models M_1 and M_2). The trained models are then evaluated in fitness space. If M_1 outperforms M_2, then datasource S_1 is considered to be of better quality than S_2. This is explored further in Sec. 4.4.1.

1.5. Thesis Organization

The remainder of this thesis is organized as follows. Some contextual information is presented in Sec. 2.1 and Sec. 2.2. Prior, related work to the previously mentioned classification and optimization problems are discussed in Sec. 2.3. Finally, the proposed optimization frameworks and methodologies are presented in chapter 4. Additionally, prior publications arising from this work are presented in Sec. 1.6.

1.6. Publications Arising from this Thesis

1. Panchapakesan, A., Abielmona, R., Falcon, R., & Petriu, E. (2018). Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations. In Advances in Artificial Intelligence: 31st Canadian Conference on Artificial Intelligence, Canadian AI 2018, Toronto, ON, Canada, May 8–11, 2018, Proceedings 31 (pp. 265-271). Springer International Publishing.
   This publishes the results presented in Sec. 4.1.
2. Panchapakesan, A. (2018, Oct). Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations. Paper presented at the 2018

workshop of Canadian Tracking and Fusion Group, Ottawa, ON, Canada.
This publishes the results presented in Sec. 4.2.

3. Panchapakesan, A. (2019, Mar). Improving Shipping Container Damage Prediction Through Machine Learning based Level 4 Information Fusion. Poster presented at the 2019 Engineering and Computer Science Graduate Poster Competition, University of Ottawa, Ottawa, ON, Canada.
This publishes the results presented in Sec. 4.3.

4. Panchapakesan, A., Abielmona, & Petriu, E. (Submitted May 2019). Improving Shipping Container Damage Claims Prediction Through Level 4 Information Fusion. Manuscript submitted for publication to International Journal of Logistics Systems and Management.
This publishes the results presented in Sec. 4.3.

5. Panchapakesan, A., Abielmona, R., Petriu, E. (2019). Optimizing Maritime Vessel Service Time with Adaptive Quay Crane Deployment Through Level 4 Hard-Soft Information Fusion. In Proceedings of 22nd International Conference on Information Fusion (Accepted for publication). IEEE.
This publishes the results presented in Sec. 4.4.

6. Panchapakesan, A., Abielmona, & Petriu, E. (Submitted May 2019). Optimizing Commercial Port Operations through High-Level Information Fusion. Manuscript submitted for publication to International Journal of Logistics Systems and Management.
This publishes the results presented in Sec. 4.4.1.

7. E.M. Petriu, R. Abielmona, R. Falcon, R. Palenychka, I. Abualhaol, F. Cheraghchi, A. Teske, N. Primeau, A. Panchapakesan, "Big Data Analytics for the Maritime Internet of Things," Canada School of Public Service Presentations - Artificial Intelligence for Insights into Regulations, Ottawa, ON, October 19,

2018.

2. Literature Survey

An overview of the relevant literature that guide the methodology in this thesis along with the prior work relating to the thesis contributions are presented in this chapter.

2.1. Port-side Vessel Servicing Operations

Relevant background information on the port-side operations involving the servicing of vessels is presented in this section.

2.1.1. Vessel Arrival and Departure Schedules

While ports do have outbound land and/or rail traffic, global shipping container traffic is primarily through marine vessel traffic. When a vessel does enter port, it must berth at one of many berthing locations at the port. The optimization of scheduling berths to incoming (and outgoing) ships based on their schedules is the well-known Berth Allocation Problem (BAP) [2, 11, 12, 13], of which there are three major variants. Ultimately, BAP is related to resource allocation problems involving the various personnel and equipment at port, in the optimization of processing each vessel, thereby optimizing port throughput.

2.1.1.1. Berthing Space

The berthing locations of a ship entering port may be discrete or continuous. Each has its own advantages and disadvantages in port operation optimization.

Discrete Berthing A discrete berth is a section of the port at which a ship may berth. It is also surrounded by an area in which the ship may not berth [2]. Thus the berthing locations are discrete along the port's quay [2]. Discrete berths at the Port of Montreal are highlighted in Fig. 2.1.

Figure 2.1.: Discrete Berths

Continuous Berthing A continuous berth is a section of the port at which a ship may berth. It is typically larger than any one ship will require for berthing space, and can accommodate multiple ships at once. Additionally, a dynamic berth allows for a ship to berth anywhere within it, which allows for multiple ships of various sizes to berth in an *ad hoc* manner, without having to allocate a separate berth for each [2]. The difference between discrete and continuous berths can be seen in Fig. 2.2.

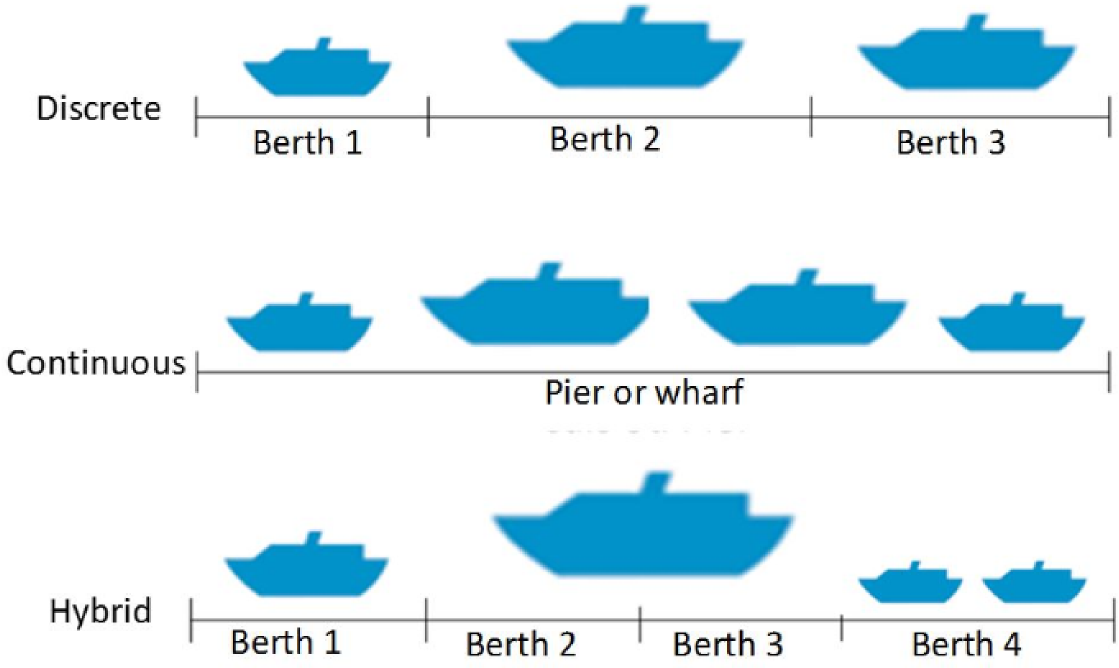


Figure 2.2.: Berth Types [2]

2.1.1.2. Vessel Arrivals

Typically, approximate vessel arrival times are known by the destination port, and the captain of each vessel continually updates the destination port on updated and more accurate arrival times. As such, the literature discusses two vessel arrival schedules, namely static and dynamic.

Static Vessel Arrivals Static vessel arrivals refer to vessel arrival schedules that are known *a priori,* a generalization over having all processable vessels within the port's waters [14]. Despite industry-wide behavior of vessels periodically announcing their updated arrival times as they approach a port, the eventual actual arrival time is rarely known *a prori* with high both high accuracy and high confidence. This is because vessel arrival schedules are subject to change, given weather patterns and other operational delays, which necessitate the sending of an updated arrival schedule. This in turn causes operational delays on the port's side.

Dynamic Vessel Arrivals Dynamic vessel arrivals refer to vessel arrival schedules that are not known *a priori,* a generalization over having only a fraction of the processable vessels within the port's waters [14, 15]. This also refers to uncertainties in vessel arrival schedules and the induced necessity to modify vessel handling processes *on the fly*, as vessels arrive.

2.1.1.3. Vessel Handling Times

Vessel handling time refers to the amount of time required to discharge, maintain, and reload a vessel, i.e. the amount of time from when the vessel berths, to when the vessel leaves the berth (and subsequently, the port).

Static Vessel Handling Time Static vessel handling time refers to cases in which the handling time for each vessel is known before the arrival of the vessel [14]. These are therefore considered inputs to any optimizer.

Dynamic Vessel Handling Time Dynamic vessel handling time refers to cases in which the handling time for each vessel is not known beforehand and must therefore be computed based on the vessel attributes and environment variables [14]. These are therefore not considered inputs to any optimizer.

2.1.2. Environmental Effects

Environmental artifacts impose operational constraints on port operations. For instance, high winds, rain, snow, and visibility affect the ability of quay cranes (and their operators) to discharge a berthed vessel; storms and rough seas affect ship piloting and cargo integrity; and geographical artifacts (such as earthquakes, storms, etc) and environmental artifacts (such a traffic flow, road design, etc) affect shipping container and cargo integrity while the container is in transit, terrestrially outbound from a port. Thus, mining correlations between environment artifacts and damage claims can help identify causal relationships between certain environmental artifacts and damage claims. Identifying these would help improve risk profiling when investigating the cause of container damage, when a claim is submitted. The specific sources of such data are further discussed in Sec. 3.1.

2.1.3. Vessel Loading and Unloading and Container Storage

Vessel loading and discharging are at the core of port operations, optimizing which, is of paramount concern. Indeed, these operations are associated with their own optimization parameters, which rely on the optimal storage conditions of the shipping containers, the presence of hazardous materials, the duration of time for which the containers are expected to stay within the port before being loaded onto another ship, or rail or a truck for delivery. For instance, storing containers by outbound date causes intra-port traffic bottlenecks, leading to sub-optimal performance [16, 17, 18]. Similarly, vessel loading and unloading are well studied problems, that account for vessel balance and cargo priority [19, 20]. Note that while the literature typically discusses containers in twenty-foot equivalent units (TEUs), the specific operational handling times of shipping containers are agnostic to the actual shipping container size, as long as the collection of shipping containers to be processed is homogeneously sized.

2.1.4. Summary

While vessel inbound and outbound schedules are typically known to ports, the optimal berth and resource allocation can not always be computed *a priori*, as unforeseen effects of environmental affects and operational variances can cause significant deviations from the predetermined, ideal schedule. Instead of attempting to predict all possible delays, dynamically reacting to updated vessel arrival schedules, container storage locations, and port congestion indicators paves the way to investigate the optimization of port operations to maintain port-side throughput. Such flexibility requires ingesting data from different sources and combining them to form a coherent operational model. There are many models for such data fusion, which are examined in the following section.

2.2. Data Fusion

2.2.1. Definition

Data Fusion can be defined as “the process of utilising [sic] one or more data sources over time to assemble a representation of aspects of interest in an environment” [21, 22, 23]. It is a process that allows for the ingestion of information (of various degrees of redundancy) from multiple sources and over multiple communication modalities, in order to formulate a more comprehensive description of the operational environment. Over time, however, Data Fusion has grown to encompass not only situational awareness (SAW), but also threat assessment, course of action generation, impact assessment, measures of effectiveness and performance, process refinement, etc. These are explained in the following subsections.

Many models for data fusion have been developed for use in various applications.

2.2.2. Endsley's Situation Awareness Model

According to the Endsley Model [21, 24, 25], situation awareness can be captured in the three states discussed in this section, namely perception of environmental elements, comprehension of the perceived elements, and projection of future states. This model of situation awareness works in conjunction with defined goals and the available equipment and infrastructure to interface with decision makers and actuate decisions made with judgment accumulated over training and experience. The resultant environmental change is then reported in a feedback loop to inform not only the perception of the new state of the environment, but also to correct any inaccuracies in the projection of future states (see Fig. 2.3).

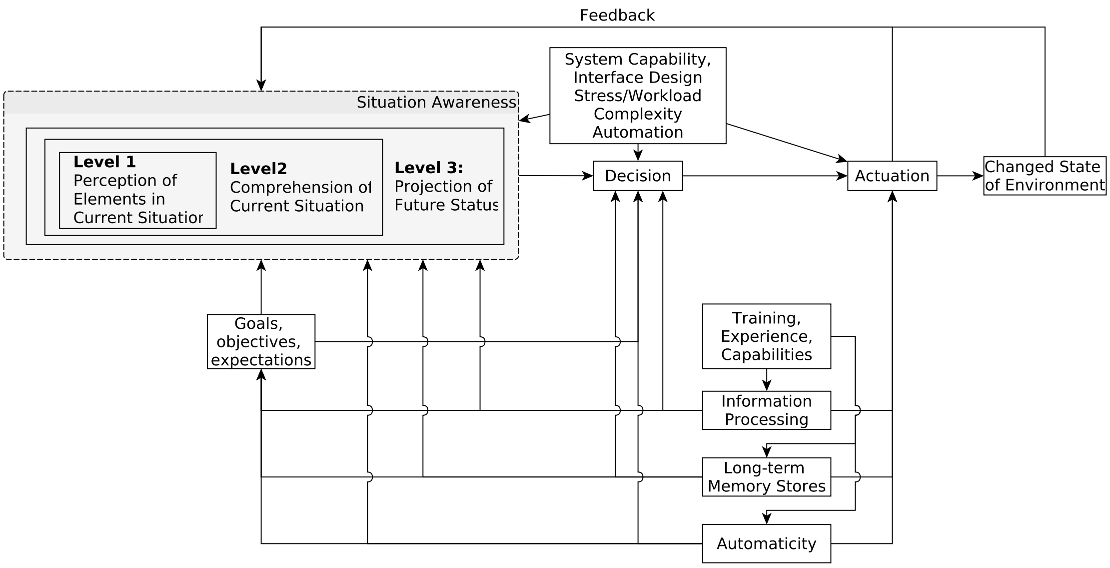


Figure 2.3.: Endsley's Situation Awareness Model [3]

2.2.2.1. Level 1: Element Perception

This level deals with perceiving and detecting and extracting elements of interest from the environment. These could include agents (such as living creatures such as people, animals, etc; and mobile platforms such as aircraft, ships, terrestrial vehicles, remotely controlled entities, etc) and environmental entities (such as geographical artifacts including mountains, cliffs, and paths; biospherical artifacts such as wooded areas, animal nests and trails; and relevant environmental aspects such as atmospheric CO_2 levels, etc). This is the first step to making sense of one's environment in order to develop a plan of action to move towards accomplishing the defined objectives [3].

2.2.2.2. Level 2: Situation Perception

This level deals with identifying the entities detected in Level 1, and understanding the various relationships between them. For example, the following fall under the scope of Level 2:

- detecting pursuit and evasion
- detecting imminent threats (such as incoming missiles, intruders, etc)
- detecting convoy behavior
- detecting adversarial and cooperative behavior

The processes in this level have more to do with sensemaking and comprehension of the behavior of the various environmental entities. It is at this level (of perception) that many mistakes are made, as it has to do with evaluating the current state of the components of the environment that are relevant to achieving the defined objectives [3].

2.2.2.3. Level 3: Future State Projection

Given the relationships between the elements detected in Level 1, as detected in Level 2, Level 3 aims to compute the state of these elements in the future. Thus, prediction and estimation of the future states of various elements falls within the scope of Level

3. With adequate predictions of the likely future states, it is possible to assess these future states in order to adequately address and respond to them. This includes predicting the level of risk posed by the environmental variables upon entities of interest, and computing the impact force (the amount of perceived damage, and the resource requirements to fix the projected damage) thereupon. It also affords the evaluation of a proposed set of actions, to determine their efficacy in moving towards the defined objectives [3].

2.2.3. State Transition Data Fusion (STDF) Model

The State Transition Data Fusion (STDF) model [21] represents and describes the world as a set of states with transitions between them. A state is described as having the following properties:

- being spatiotemporally bounded
- capturing the world in a set of variables that are relevant to the problem at hand
- describing those variables no more or less than sufficiently, as required to understand and solve the problem at hand
- identifying the persistent elements of the environment. These could be static object states and/or transitions, or cycles in the directed graph representation of state nodes connected by transition edges. For instance, though the low-level mechanics of driving a car cannot be described as very static, the state of driving a car from a source to a destination can be captured in a dynamic state, as it is in a closed cycle involving the various actions associated with driving a car.

The STDF model maintains this notion of states and transitions over multiple levels of abstraction. At each level, the current state describes either objects, inter-object relationships, or scenarios comprised of multiple interacting objects; and at each level, a formal language is used to describe the transition between the entity states at the current time and at the next discrete time step [4].

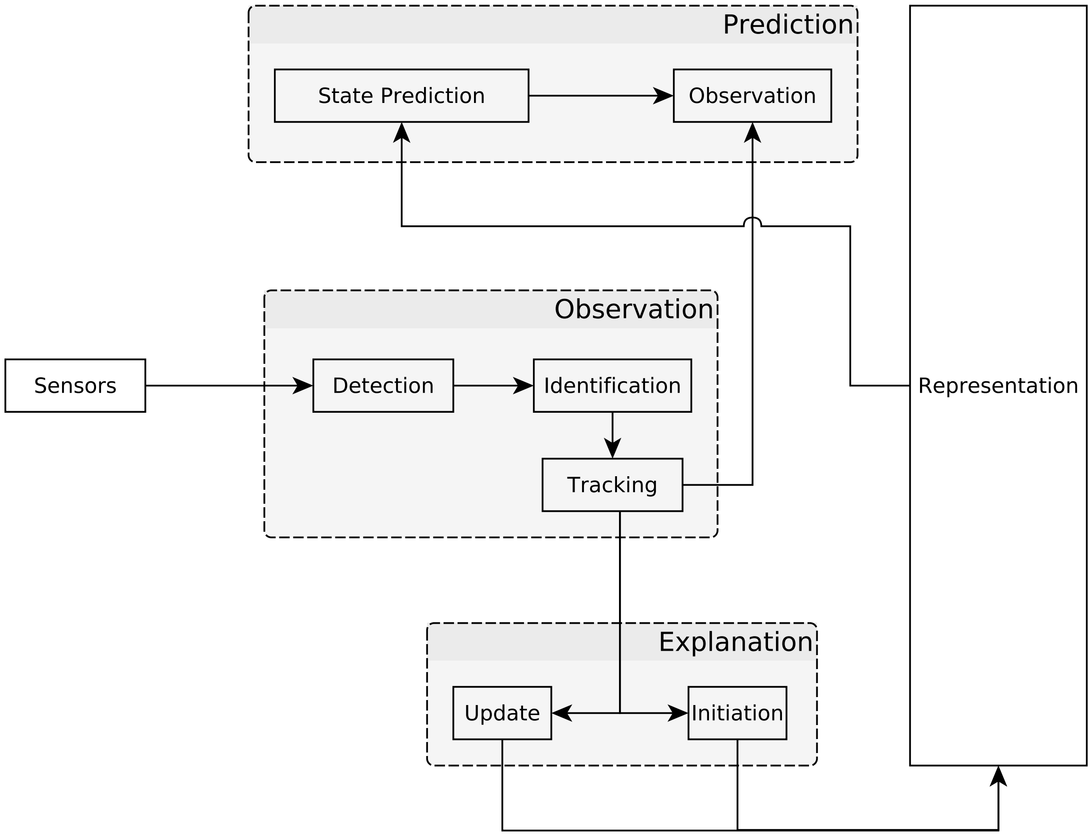


Figure 2.4.: State Transition Data Fusion Model [4]

2.2.4. JDL/DFIG Model

The JDL/DFIG model [21, 26, 27, 28] (created by the Joint Directors of Laboratories (JDL) and the Data Fusion Information Group (DFIG)) captures the different levels of abstraction in data fusion as different levels, with data and control flow between the different levels. These levels and their interactions are seen in this section.

2.2.4.1. Level 0

This level of the DFIG model pertains to gaining accurate readings of any incoming data. For example, ensuring that proper digital signal processing is performed to receive a proper signal from a satellite or a radar falls within the scope of Level 0. This can be seen in Fig. 2.5.

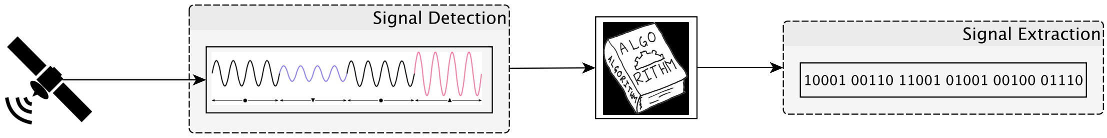


Figure 2.5.: Level 0 Process

2.2.4.2. Level 1

This level of the DFIG model pertains to the extraction and representation of object properties and states. For example, identifying parts of an object (such as the amount of remaining fuel in a ship), and the current state of an object (the car has a flat tire) both fall within the scope of Level 1. This can be seen in Fig. 2.6.

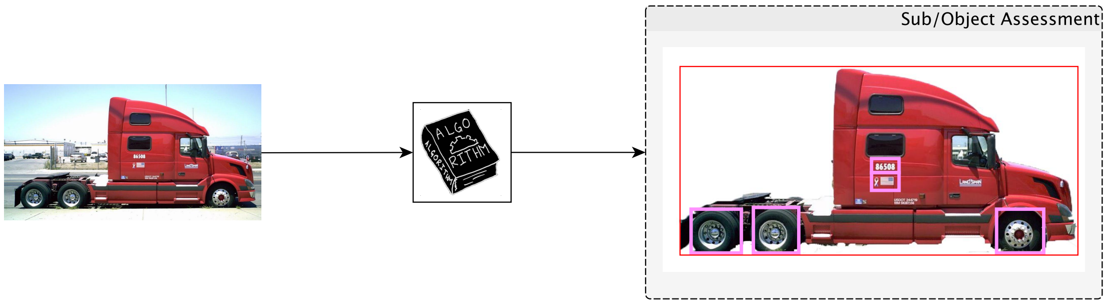


Figure 2.6.: Level 1 Process

2.2.4.3. Level 2

This level of the DFIG model pertains to understanding how the different entities relate to each other and any events of interest (EOIs) currently under study. Additionally, predicting entity states (the future position, heading, and velocity of a ship, the amount of remaining fuel it will have, etc) falls under the scope of Level 2. This can be seen in Fig. 2.7.

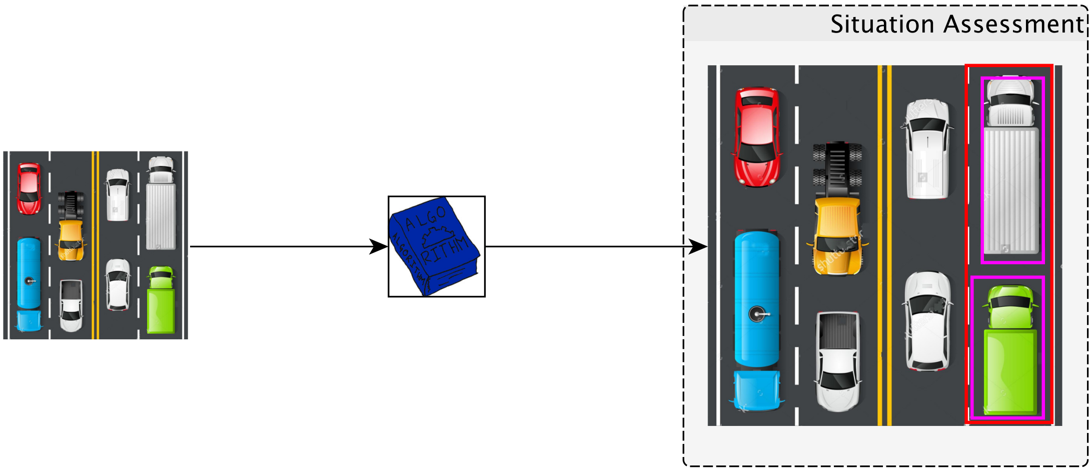


Figure 2.7.: Level 2 Process

2.2.4.4. Level 3

This level of the DFIG model pertains to evaluating threats and generating courses of action by predicting their effectiveness in future states and recomputing associated threat metrics. Given the information computed in Level 2, Level 3 attempts to compute the impact on the future states of the entities identified therein, on the states of entities of interest (e.g. equipment and infrastructure, local environment, personnel, etc). Also within the scope of Level 3 is the computation a threat assessment (TA) and the generation of courses of action in response to the threat, once the impact assessment has been computed. This can be seen in Fig. 2.8.

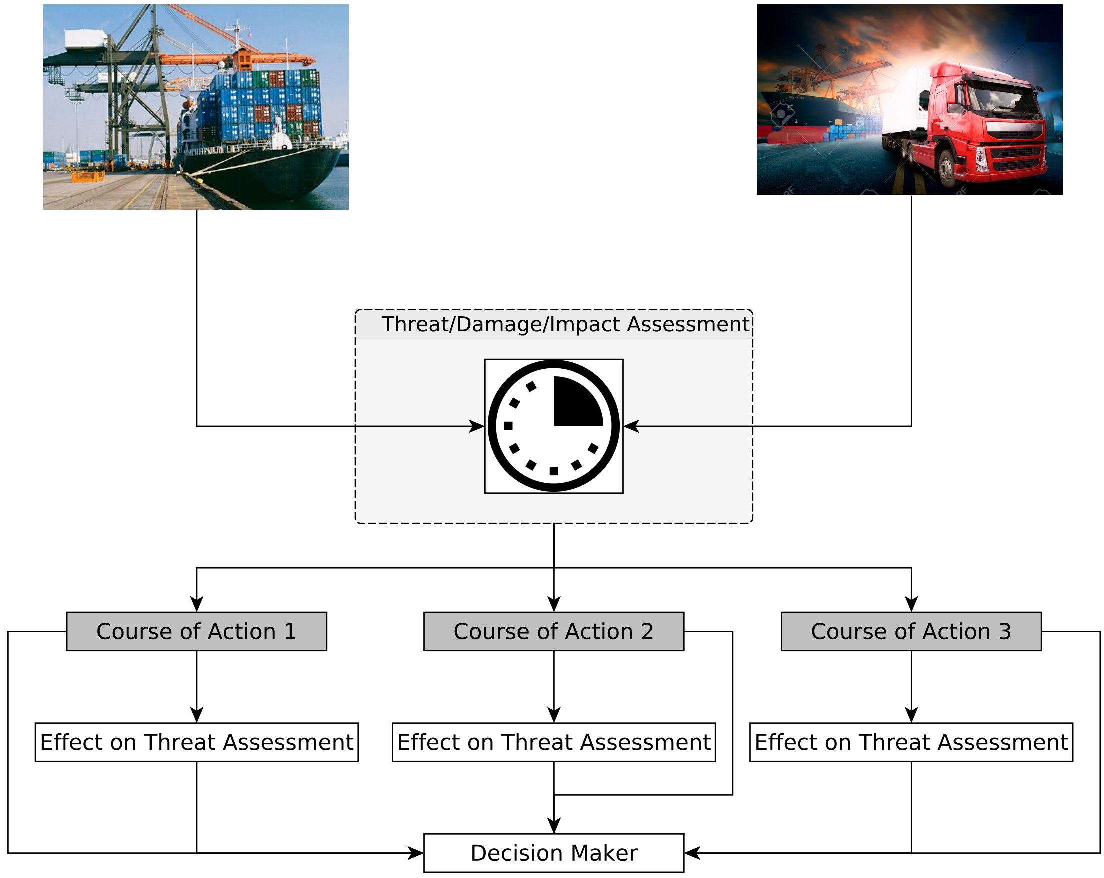


Figure 2.8.: Level 3 Process

2.2.4.5. Level 4

This level of the DFIG model pertains to the refinement of the processes involved in Levels 0-3. Level 4 entails the optimization of the processes involved in:

- data acquisition and processing, including
  - positioning and calibration of various sensors from which to acquire sensory data about the environment
  - selection of data sources based on the integrity, veracity, completeness, and relevance of the data

   - choice of algorithms with which to collect and analyze data from the configuration of data sources

- threat assessment
- course of action generation

These are achieved by analyzing the correlations between past actions, and their effects as measured by various measures of effectiveness and performance. Thus, inefficiencies in the current process are discovered and addressed by feeding back into program modules operating at Levels 0-3. This can be seen in Fig. 2.9.

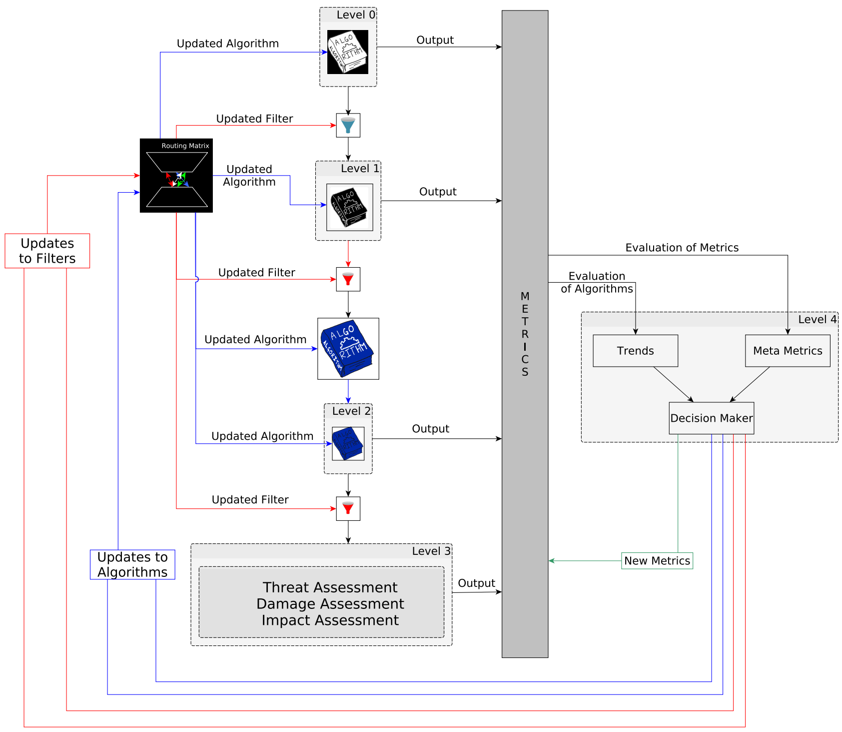


Figure 2.9.: Level 4 Process

Given a network of sensors, a Level 4 module may choose to reposition the sensors in order to improve coverage, to minimize the energy required to reposition sensors, etc. It may also choose to turn on or off certain sensors based on the information gain, relevance, and integrity and veracity of data provided by each one. Such a

Level 4 module may also decide to change the algorithms with which certain data streams are processed, so that noisy data are processed with more robust algorithms, while relatively clean data are processed with fast and naive algorithms. These decisions are made to optimize Measures of Effectiveness (MOEs) and Measures of Performance (MOPs).

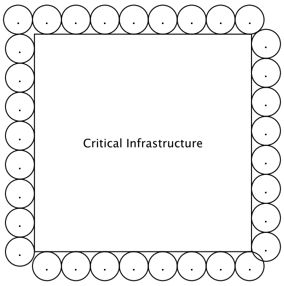
Measures of Effectiveness (MOEs) Measures of effectiveness typically fall under the broad definition of (IFE) and its metrics [21]. These differ from MOPs in some key ways. While a fast algorithm will have a high-scoring MOP, it mat have a low-scoring MOE if it returns results when they are no longer needed. For instance, if the fastest classification algorithm correctly classifies shipping container damage, it is only useful to Bruce if it is able to return the classification outcome before Bruce receives an insurance claim on the container. Therefore, while the algorithm's accuracy affords it a high MOP, it will have a very poor MOE if the results are not timely.

Another key difference between MOPs and MOEs has to do with an algorithm's robustness, or its ability to cope with variations in real-world data. While a high-performant algorithm may have a high accuracy, yielding a high-scoring MOP, the algorithm may still have a low-scoring MOP if the accuracy was computed on a dataset with extreme sample bias, leading to poor algorithmic bias when tested with unseen data that lies sufficiently far from the mean in the training set. This inability to maintain its performance in the face of variation in the real-world data would cause the algorithm to have a low-scoring MOE.

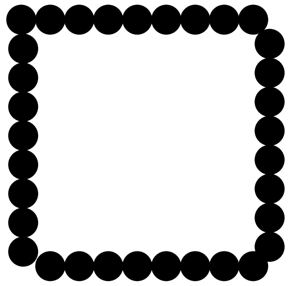
IFE is computed as shown in Eq. 2.1.

$$\text{IFE} = \text{Information Gain} \times \text{Quality} \times \text{Robustness} \tag{2.1}$$

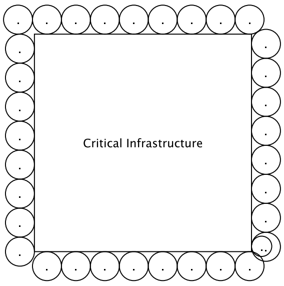
Information Gain This refers to the amount of new information brought into the knowledge base as a result of fusing a given data source (or otherwise performing any other fusion operation). A sensor network with a wider coverage will therefore afford a higher information gain than its low-coverage counterpart. Similarly, the choice to not activate a certain sensor node based on redundant coverage (i.e. the segment of the environment covered by the sensor was already covered by some subset of the already activated sensor nodes) is based on the notion of information gain, i.e. that no new information will be collected by activating that sensor node (assuming that all sensor nodes have the same sensor capabilities). This can be seen in Fig. 2.10.



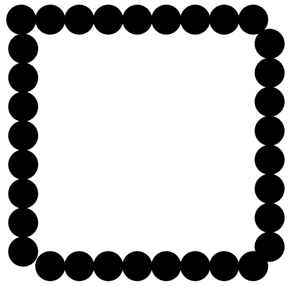
(a) A sensor deployment to monitor a critical infrastructure



(b) Coverage of sensor deployment in 2.10a



(c) Note the redundant sensor at the lower right hand corner, offering no information-gain



(d) Redundant sensor offers to additional coverage from 2.10b

Figure 2.10.: Deactivating a Redundant Sensor Node Does not Decrease Information Gain

Information Quality This refers to the integrity of the received data, which fundamentally differs from Information Gain. For example, a malfunctioning (i.e. malfunctioning refers to transmitting with high sensor noise) sensor node in a low-coverage area will have high information gain as it transmits previously unknown information. However, the noise in its instrumentation causes it to yield data that is not very representative of the real world. This means that despite having high information gain, the low sensor accuracy causes low information quality. This can be seen in Fig. 2.11.

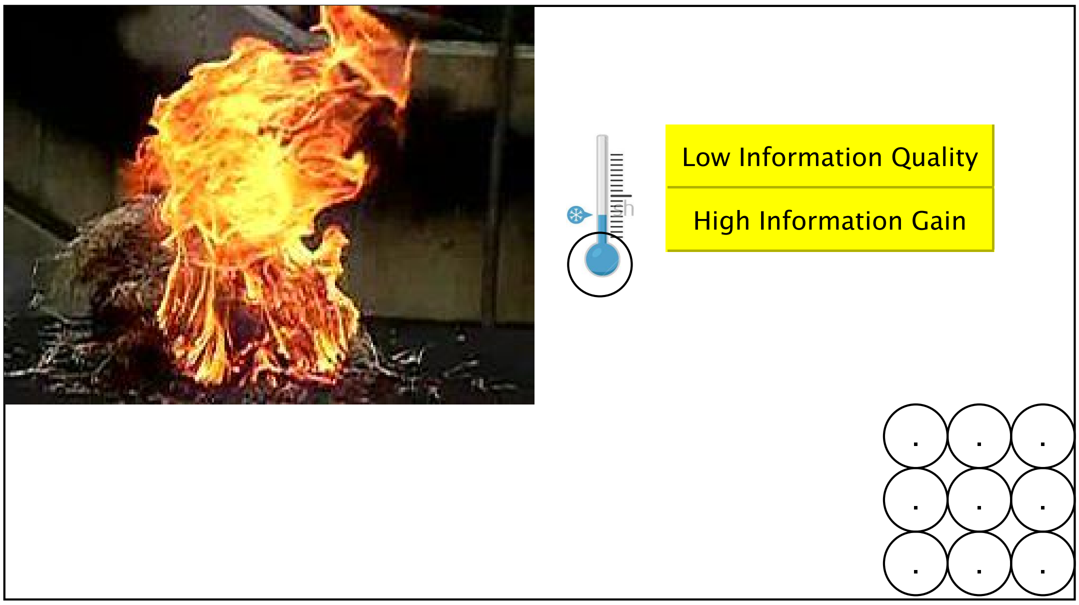


Figure 2.11.: A Sensor Node Reporting Low Temperatures Near an Otherwise Unobserved Fire has Low Information Quality Despite having High Information Gain

Robustness Data fusion robustness refers to its tolerance to noise, and its ability to generalize to other scenarios to which it may be applied. For example, an information fusion system that performs well in a maritime scenario involving multiple vessels in the North China Sea but fails when the same scenario is run in the Pacific Ocean is limited in its capabilities, and requires to be tuned for each instance.

Robustness also refers to the ability of an information fusion system to tolerate noisy and/or incomplete data. Therefore, an information fusion system that performs well even under conditions of low coverage (a sensor network with low information gain) and noisy and/or inaccurate data (a sensor network with low information quality), is considered to be more robust.

Measures of Performance (MOPs) Measures of Performance (MOPs) refer to how quickly and accurately the information fusion system performs. This encompasses such metrics as:

- device uptime
- resource utilization
- prediction accuracy
- communication latency
- data compression ratio
- resource requirements to reconfigure the sensor network when necessary
- sensor network adaptability (the ability of the sensor network to continue at high performance levels when for example, a sensor node goes offline)

2.2.4.6. Level 5

This level of the DFIG model pertains to managing the data fusion process within the context of the human operators that interact with it. Within the scope of Level 5, are changes to the structure of the dissemination of information and the decision making hierarchy, user interface design and human-computer interaction, and information compartmentalization and access.

2.2.5. Summary

Level 4 of the JDL/DFIG model (see Sec. 2.2.4.5) will be used to drive the optimization earlier identified problems. Further, the MOPs and MOEs of the used machine learning algorithms will be used to guide the improvement of not only their individual performances, but also the performance of any combined, ensemble methods that may be borne from this exercise. This will likely result in improved performance in not only port operations, but also in the optimization of port performance. Yet, before combined performance can be evaluated and tuned, the performance of simpler models on individual problems must be evaluated in order to establish a benchmark. These are analyzed in the following section.

2.3. Maritime Port Optimization

Research into the factors associated with container damage and claims is not very well represented in the literature, as opposed to ship damage or other related problems. The literature is also very sparse in the application of machine learning techniques to this problem, which constrains the scope of the current knowledge. Accurate container damage predictions enable discussing the selection and dynamic selection between data sources and algorithms used to process the data therefrom. This information may be used in a decision support system that can then be integrated into a terminal operating system (such as N4 [29], used to track shipping container positions around the port from the time of entry to the time of exit) to help identify root causes of container damage, to help alleviate bottlenecks from data collation and analysis.

Though this particular problem is not very well researched, similar problems indeed have been, and a subset of the insights and methodologies presented in the relevant literature is applicable to this problem. These are presented in this section.

2.3.1. Surveying Domain Experts

Surveys of Taiwanese domain experts reveal a taxonomy of risks posed to refrigerated containers in their port-to-port travel with the following three categories:

Operational Risk including improper temperature and ventilation settings

Hardware Risk including a malfunctioning container thermostat

Consignor's Risk pertaining to any errors made on the part of the consignor in slow cargo loading, leading to cargo spoilage, etc

Risk factors involving human error had the highest combined perceived (by domain experts), severe (the monetary loss in the affected cargo), and frequently occurring risk to shipping container damage [30]. Thus, human error will be modeled in this study.

A study of the determining factors of consignors' port choice highlights attributes correlated with such decisions [31], including the consignor's proximity to the port (which is correlated positively with their port of choice, as increased container travel times increase the logistic shipping costs and the probability of en route damage), the annual traffic through the port, and the number of shipping routes served by the port. Since the present study only models one port, the latter two attributes are less relevant.

The port choice behavior [31] is captured in three models that were generated to be true to the survey data, namely:

Basic Model includes parameters for alternative ports and routes, frequency of weekly port departures, and travel time and cost. This model deems travel time (and cost) of a container to port to be the most important features.

Experienced Model decides between alternative port choices based on previous experience. This model uses the number of possible alternative routes from the consignor's facility to the port as the primary deciding factor.

Competitive Model decides between alternative ports based on a holistic consideration of all port properties. Travel time (and costs) to port are again the most important features, but can be offset by the number of routes an alternative port services, or the weekly departure frequency.

Given the arguments for the consignors' selection of the nearer ports, container damage risks during maritime travel were included in the present study. The primary risk factors in travel stem from:

- sea state and weather conditions along the ship's voyage
- human error induced by low crew morale
- cognitive operational alertness, etc. [32]
- the ship's pilot's skills in safely berthing the ship
- the health and operational integrity of the ship and the equipment therein equipment
- crew morale and skill
- the power, health and operational integrity of the tugboat
- the tugboat pilot's skill level
- the skill level, attitude, and morale of the linesmen personnel involved in ship berthing
- the robustness, availability, and accessibility of docking equipment such as wind lasses and line handling boats
- port management policies, including marine piloting laws, ship lane rules, etc.
- the physical and mental health of operating staff
- weather and geography [33]

Although these factors are important, incomplete Port Policy and Procedure documents do not standardize marine critical procedures for pilots in the the port's waters. Since the associated incident reports are confidential, this information cannot be used in the current study. Yet, probability distributions that model other factors pertaining to the operational capabilities of personnel and equipment were included within this study.

2.3.2. Modeling and Simulation

A case study of the voyage of a ship destined for Seattle in late October, 1998 [34] discusses mathematical constructs and simulation software in their abilities to predict kinematic properties (including pitch and yaw) of a ship at sea, subject to prevailing sea state and weather patterns. Two software tools are used:

FREDYN This is a ship motion simulator that accurately predicts the parametric roll angles of a ship, as subjected to winds, waves, etc, while at sea. Yet, it did not accurately predict variations in ship speed and roll amplitude, tuning which could yield better results. Additionally, it is specific to measuring and predicting the various forces upon, and the kinematics of a ship at sea [34]. Thus, it is too narrow for the present study. Yet, the parameters used to guide the investigation have broader applicability and are used in this work, including:

- wind speed
- wind direction
- hurricane rating
- wave height
- wave dissipation
- wave interaction
- wave propagation/swell

- wave confusion

Some of the data sources used were found to be publicly available, and were therefore included in this work, along with other data sources, including:

- Global sea state data from the National Oceanographic and Atmospheric Administration (NOAA) [35]
- Local weather data from Environment Canada [36]
- Global weather data from (NOAA)

LAMP LAMP (Large Amplitude Motion Program) is a numerical investigation tool, which accurately predicts:

1. the roll angle of a ship
2. roll event buildup (the accumulation of rolling momentum from continuous the side-to-side rolling of a ship)
3. the changing of the roll period

It is also noted that LAMP is sensitive to the topology of a ship's hull, its weight distribution, and roll damping coefficient (a function of the sea state, wave characteristics, ship kinematics, and ship topology), requiring specific characteristics of ship bow flares in order to ensure accuracy [34]. Such preconditions are difficult to guarantee, making such analysis out of the scope of the current work.

It was noted in the investigation that post-Panamax class ships were fitted with a lashing bridge to improve a ship's cargo capacity and efficacy in ensuring cargo safety. Yet, these ships face challenges from the same environmental sources (namely weather and sea state) in transporting cargo between sea ports [34].

While these studies highlight important features of a shipping container along its voyage on board a ship, and the relevant modeling and simulation software, they do not use any Computational Intelligence (CI) [37] methodologies or data-driven approaches to compute feature importance.

Data for such methodologies (e.g., from Lloyd's Register [38]) can be used to extract ship characteristics and correlate them with maritime accidents. Indeed, Kelangath et. al. [39] use such historical data to construct a Bayesian Network, which captures dependence relationships between the various ship and cargo features, and the type and intensity of an accident to the ship. Traversing with off-the-shelf software (such as GeNIe [40]) correlates accident type and intensity to ship features including ship age, type, and location (whether the accident occurred at sea or at port), cargo type (was the cargo considered hazardous or dangerous, etc), and weather adversity.

From this data, it was determined that ship age, on board hazardous cargo, time of loading, and when the ship was at sea, most highly correlated with the occurrence of an accident. These features are therefore included in our data.

Computer simulations have also been used to study the effects of weather and visibility on the time requirements for loading and unloading oil tankers in a Chilean port [41]. Wind, visibility, precipitation, and the buildup of ice, were found to determine the time requirements to load and unload an oil tanker. These factors also determine the safe speed limits for incoming and outgoing ships and intra-port vehicles. For instance, berthed oil carriers are not cleared to leave the port, and new tankers are prohibited from entering the port when wind speeds exceed 15 m/s. Similarly, reduced visibility impedes ship approach and restricts new departures. The effects of ice buildup within this model are limited to the thickness of ocean surface ice, not including the effects of ice on roads within the terminal which may affect the movement of intra-port vehicles and personnel. This model also ignores effects of rain or snow on terrestrial and maritime vehicles and their piloting. These attributes are used in a discrete event simulator, along with the probability densities of environmental behavior learned from historical data (provided by the Chilean Government), to determine port storage capacity. The attributes included in these models are also included in the present study, along with marine and terrestrial precipitation (rain and snow).

Discrete event simulators typically struggle with computational deadlock when processing such large-scale simulations. Bielli et. al. address this in their Container Terminal Simulator [42], which simulates events and entities (equipment, vehicles, and human agents) that are common to commercial maritime ports, and operations including events involving Roll-On/Roll-Off ships (Ro-Ro ships), Load-On/Load-Off ships (Lo-Lo ships), quay cranes, shunting trucks (and Fatuzzis), and large gantry cranes to move shipping containers within the storage yard. The software notably focuses on simulating details of port-side personnel and vehicular behavior, with which port management and safety policies are evaluated, on metrics such as average equipment utilization, containers moved per simulation, etc., with additional parameters that may be calibrated. While this software makes advances in distributed, discrete event simulation as applied to commercial maritime ports and the container yards therein. However, it does not account for risks stemming from behavioral effects (such as human error) or equipment failure; nor does it account for the effects of weather, geography, or sea state, as others have done.

Other numerical simulations have studied the effects of ocean states on seafaring vessels [43, 44], while others still have used such techniques to optimize shipping container placement in storage yards [45], as well as in assigning quay cranes to vessels to handle increased process load [46].

2.3.3. CI Methodologies in Maritime Operations

While modeling and simulation tools evaluate policy efficacy against ship damage and discover root causes of delays, etc., few publications explicitly discuss the root and/or composite causes of shipping container damage by applying CI techniques [37] to a data set. One study compared the efficacy of decision trees in predicting the total loss and damage to a ship, given its attributes [47], including:

- CHi-squared Automatic Interaction Detection (CHAID) trees, which compound multiple variables together if their individual predictive abilities fall below a parametric threshold [48]
- QUEST trees, which performed well, but did not generalize well to more complex problems, and had already sustained scrutiny for a lack of reliable convergence [49] and a lack of improvement in its accuracy over Davenport's q method, upon which it is based [50]

CHAID trees had the highest predictive accuracy, and a later study by the same author [51] improves upon its prediction accuracy. However, this algorithm works only with multi-class classification problems (and not binary classification problems), and are therefore infeasible for the current study. Yet, this supports the use of a binary class decision tree algorithm (such as CART), which was also used in the former publication. This is further supported by the use of an information-gain based decision tree to classify the root cause underlying a maritime casualty [52], among six classes, namely equipment failure, human error, adverse weather conditions, force majeur, and a nominal "other" class. The classification is performed with ship's attributes including ship age (older ships were more likely to have an accident), the weather and geography at the time of the incident (adverse weather conditions and rougher seas were more likely to induce an accident. Additionally, ships in shallower waters were more likely to be grounded), the initial cause of the accident (human error was the leading underlying cause of accidents), and damage sustained by the ship and loss of human life. These attributes and their effects on the likelihood of a maritime casualty incident were used in the current study, to generate realistic data with which to train classifiers; as have relevant attributes from the previously discussed studies.

2.3.4. Other Relevant CI Methodologies

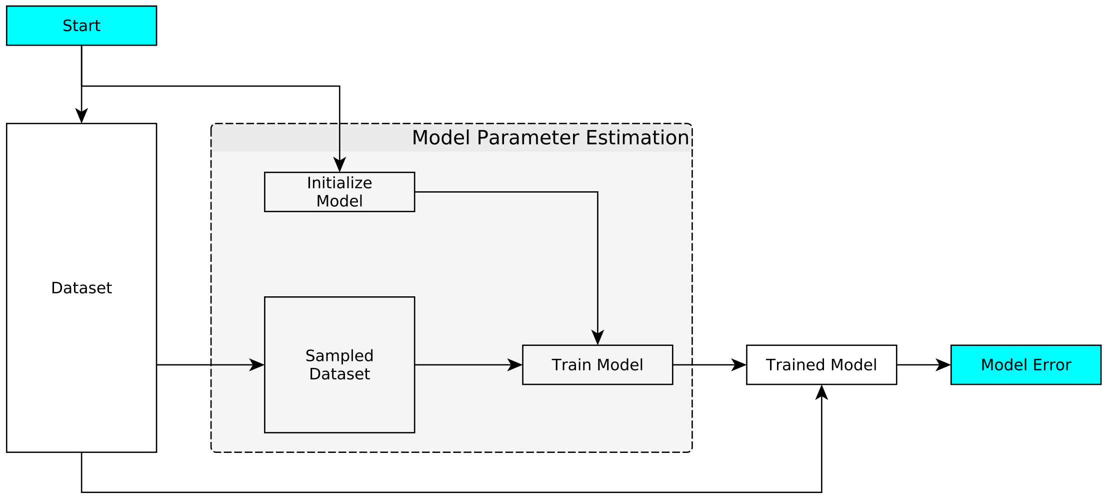
Once multiple CI models have been trained to classify shipping container damage, an implementation of a Level-4 algorithm would consider the historical performance of each of these models and attempt to learn correlations between features of the data and classifier performance. This would allow for the dynamic selection between classifier algorithms on unseen data, to boost the overall performance of a composite system comprised of heterogeneous algorithms, each with its relative strengths and weaknesses [21].

The problem of tuning model parameters has been well studied with Sequential Model-based Optimization for General Algorithm Configuration (SMAC) [53, 54], Random Sample Consensus (RANSAC) [55, 56], Random Online Aggressive Racing (ROAR), etc. RANSAC excels at estimating model parameters and detecting outliers in the data. This is achieved by repeatedly sampling the training data, training a model on the sample and reporting the error on the trained model. In each (independent) iteration, the model starts from a random initial state (as dictated by the learning procedure of the model). Finally, the trained model (trained on the sample of the training data) is tested against the entire dataset and its prediction error is recorded. Over multiple iterations, the trained model with the best prediction error is reported as the best general model to estimate the data (this process is illustrated in Fig. 2.12). This approach of searching for the model with the best error is especially useful when attempting to fit a model with no prior solutions, in the absence of a known maximal error tolerance threshold. However, RANSAC by itself is capable of only estimating the parameters of a given model and needs to be extended to include a heterogeneous collection of algorithms as well. Additionally, since the distribution of outliers in the dataset is unknown and the training on this dataset was originally performed on 70% of the data [1], RANSAC's false positive outlier detection probability increases. This can be remedied by increasing the size of the subsample upon which the model is trained in each iteration of the algorithm, which negates the improvements in speed that RANSAC offers.

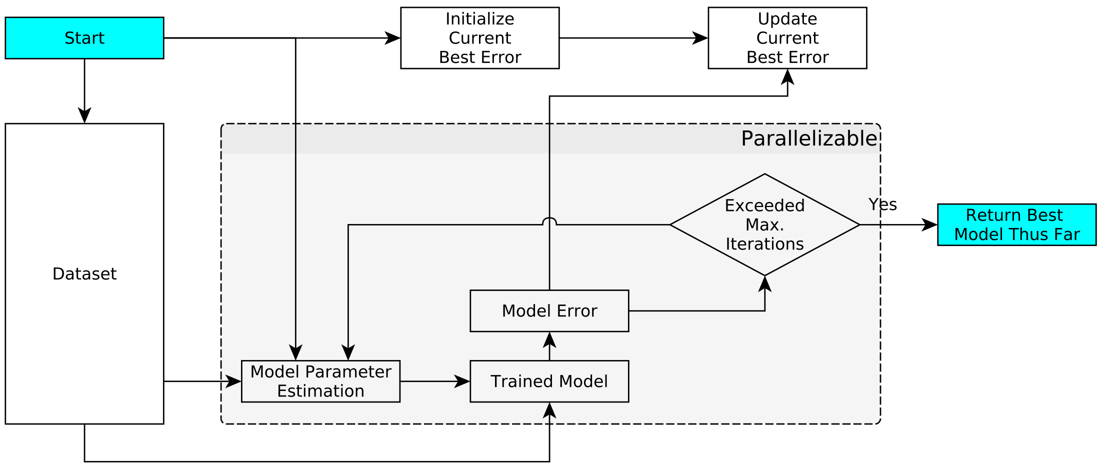
In contrast, ROAR uses the entire dataset and iteratively evaluates randomly selected parameter configurations (as seen in Fig. 2.13). In each iteration, the parameter configurations are chosen uniformly at random, rather than with any method with analytic intelligence. In each iteration, ROAR compares the performance of the model on the selected parameters to previously tested parameters and either accepts or rejects the new parameters based on its test error. However, this has been criticized for being demonstrably too aggressive [54, 57], and has therefore been excluded from this study.

While such algorithms as cross validation perform an exhaustive grid search on a model's parameter space to find the global best parameter vector, ROAR takes a more probabilistic approach whose limiting case as the number of iterations increases, is cross validation (as illustrated in Fig. 2.13). However, the probabilistic search is performed in a uniform random manner in which each iteration is independent of the rest and therefore wastes all residual information gain from previously visited points in the search space. Typically, such information can be taken advantage of in the form of linear or nonlinear algebraic analysis or regression. When faced with the ineffectiveness of such methods, other methodologies such as Genetic Algorithms randomly combine portions of good solutions (points in the parameter space, in this case) in the hopes that this would lead to exploring better points in the search space (this has been proven in John Holland's Schema Theorem [58]).

While ROAR has been shown to indeed perform well, it does still suffer from its own limitations in disregarding useful, residual information from previous iterations to guide the search. In contrast, SMAC repeatedly subsamples the dataset and trains a separate instance of a given model on each sample and computes the test error on each (similar to RANSAC). Using this information, it attempts to fit a "metamodel" to predict the test error, given a point in the parameter space, which it then uses to guide the search within the parameter space [53, 54, 59, 60]. This guidance improves the probability with which high fitness points in the search space are explored. Yet, ROAR, SMAC, RANSAC, and other similar algorithms output one tuned classifier that outperforms all others on a given dataset rather than use a collection of trained models that can be dynamically deployed. Along the same lines of investigation used in researching neural networks (i.e. to model the behavior of the human brain through interconnected neurons), investigating the use of an ensemble of multiple models (as has been done herein) attempts to model the functionality of the human brain as a collection of highly specialized modules [61]. To the best of our knowledge, this is the first study to investigate the dynamic deployment of multiple trained classifier models to accurately classify shipping container damage.



(a) Model Estimation



(b) Iterative RANSAC Algorithm

Figure 2.12.: The RANSAC Algorithm

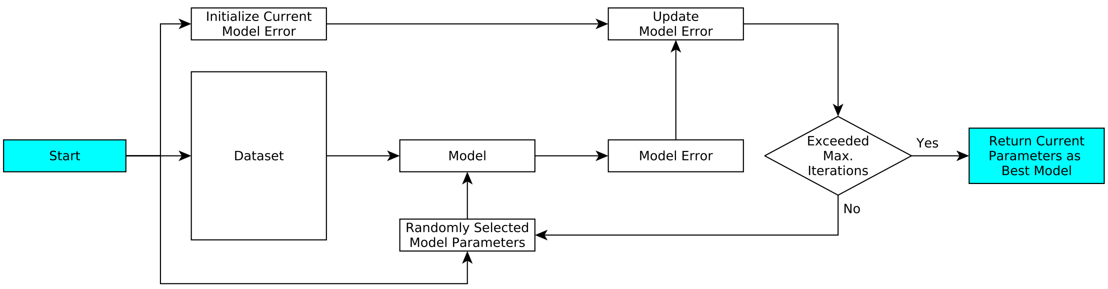


Figure 2.13.: The ROAR Algorithm

2.4. Fuzzy Systems

Fuzzy controllers have been used to dynamically allocate resources in large-scale job scheduling environments with strict job completion deadlines [62]. This was performed by phrasing the job scheduling problem as a prediction optimization problem of job completion times given resource availability. The estimator that predicts job completion time is formulated as a fuzzy system that considers the job requirements and resource availability as inputs to output a deadline-aware scheduling for a given job. Others have suggested a continuously evolving fuzzy system to circumvent the limitations of rule bases fixed at design time, that therefore fall short of changing objectives [63]. While this methodology is impressive and powerful, the authors note that it is in excess of the requirements of problems similar to the one studied here (deploying existing resources to meet queued demand); and approaches from classical control theory will still suffice. Wang et. al. do indeed use such a fuzzy system to adaptively deploy resources to handle database load within a virtual environment to handle incoming query loads [64]. This system also updates *online*, making it reactively adaptive to dynamic workloads.

2.5. Resource Deployment

Fuzzy controllers have been used to dynamically allocate resources in large-scale job scheduling environments with strict job completion deadlines [62]. This was performed by phrasing the job scheduling problem as a prediction optimization problem of job completion times given resource availability. The estimator that predicts job completion time is formulated as a fuzzy system that considers the job requirements and resource availability as inputs to output a deadline-aware scheduling for a given job. Others have suggested a continuously evolving fuzzy

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Existing solutions to resource deployment in the maritime space suffer from being *offline*, i.e. they require *a priori* knowledge of incoming vessel schedules and their respective service load requirements. Some of these have been formulated as Mixed Integer Programming (MIP) problems [6], while others have attempted a job scheduling formulation with a homogeneous pool of processors [65]. Both methods require prior knowledge of incoming vessel schedules and service requirements, which is inconsistent with real-world practice. Moreover, these methods are unable to adapt to changing vessel schedules and operational faults such as delays in vessel arrival times (often caused by unfavorable weather conditions, etc [66]). Finally, GAs have been used in optimizing resource deployment and scheduling [67], but only in an offline fashion yet again. The methodology presented in this work proves to be robust against vessel schedule changes, while maintaining high service throughput and simultaneously minimizing operational cost.

2.6. Solution Approach

2.6.1. Predicting Insurance Claims on Shipping Container Damage

Per the brief discussion in Sec. 1.1.1, a dataset is collated and synthesized to predict whether a given container is damaged and will therefore be filed for an insurance claim. The details of the data collection and the synthesis of the dataset are discussed in more detail in Sec. 3.1 and Sec. 3.2. Once the dataset is created, many CI methodologies (made available in Python's `scikit-learn` library [68]) are used to predict shipping container damage. These results can then be improved upon by altering the learning strategy to include techniques inspired by cross-validation (see Sec. 3.4.2 and Sec. 3.4.3).

2.6.2. Dynamic Resource Allocation

The results in [69] highlight methodologies to measure maritime vessel congestion in a port's waters. These are then used to determine whether and how to alter the current resource deployment in response to projected future workload, reducing the necessity for operational speed while maintaining or increasing operational throughput. This is performed by a fuzzy system as is popularly used in adaptive resource deployment problems [70, 71].

This is performed as a multi-objective optimization considering multiple optimization objectives to adequately capture trade-offs between multiple operational decision objectives for a decision maker. The specific model used to perform this analysis are discussed in more detail in Sec. 4.4.

3. Methodology

3.1. Data Collection Methodology

The proposed data gathering methodologies for this study are outlined in this section. In order to adequately learn the cause of container damage, it is necessary to know the conditions faced by the shipping container and any ship/truck/rail it was on, during its life-cycle from the consignor to the customer. Therefore, it is necessary to ingest navigational information pertaining to the voyage of the ship the container was brought to port on. This data is not readily available and must be computed from ship track data and container damage data. The ship track data must then be fused with sea state data and local and global weather data. Finally, certain domain specific knowledge may be useful, which must be captured from experts in the industry.

3.1.1. Vessel Track Data

Vessel track data is typically found as vessel contact data, and is available from vendors such as Lloyd's Register [38]. This data is generated by an Automated Identification System (AIS) transponder on board any cargo vessel and is broadcasted periodically. Vendors (such as Lloyd's Register) then receive these broadcasted packets (through either satellite constellations, or terrestrial base stations) and store them. Therefore AIS data may be acquired for analysis from such a vendor. While there are approximately 27 types of AIS data packets, location packets are periodically broadcast, the structure of which is seen in Fig. 3.1. This shows that AIS data does contain temporal and geospatial information. Therefore, weather and sea state information can be queried at the relevant time and geospatial coordinates to ingest the corresponding environmental data.

Parameter	**Description**
Message ID	Message type identifier
Repeat Indicator	Report how many times this message has been previously sent
User ID	The vessel's MMSI[1]
Navigational Status	An identifier to determine whether the ship is powered, sailing, anchored, etc
Rate of Turn (RoT)	The turning moment of the ship - how many degrees it turns per minute
Speed over Ground (SoG)	Linear speed in knots
Position Accuracy	Accuracy of the GPS signal in the transmission
Longitude	Current position's longitude
Latitude	Current position's latitude
Course over Ground (CoG)	Current compass heading in $\frac{1}{10}$th resolution
True Heading	Current compass heading in 1^o resolution
Timestamp	The current timestamp
Special Maneuver Indicator	A binary indicator as to whether the ship is engaged in a special maneuver

Figure 3.1.: Structure of an AIS Location Data Packet

3.1.2. Container Damage Data

Container damage data is held by the companies operating at various ports. These are stored in the form of checker logs, personnel handling logs, and incident reports, all created over the course of daily operations at the port. However, this data is not accessible through the Canadian Border Services Agency (CBSA). Thus, such companies are requested to share their data, as part of a survey to be sent to these ports (see Sec. 3.1.4 for more).

3.1.3. Weather and Environmental Data

The National Oceanographic and Atmospheric Administration (NOAA) [35] publishes several global weather forecasts that can be used to describe the weather at the given time and location of a shipping container. These can thus be queried along the voyage of a vessel carrying a shipping container, to build a profile of environmental patterns faced by a shipping container along its voyage on the vessel. The forecasts and historical records are publicly available on NOAA's website, at a geospatial resolution of 0.5° latitude and longitude, and a temporal resolution of one hour. This data is then interpolated to realize the specific environmental conditions at the given exact geospatial and temporal coordinates.

3.1.4. Domain Specific Knowledge Regarding Container Damage Causes

Domain specific knowledge and experiential intuition have not been captured in any publication thus far. Since much of the data pertaining to this study is confidential and internal to the companies operating at various ports, it is plausible that these companies will refuse to share their data. As a result, such domain specific knowledge can help impute data as necessary. Thus, in order to capture and analyze such domain specific expertise, a survey has been designed, to be filled out by companies operating at terminals in Canadian ports. The survey has been reviewed by uOttawa's Office of Research Ethics and Integrity, and captures information including:

- correlations between container damage claims and
  - the consignor
  - the customer

  - the shipping line
  - the operator discharging the inbound ship
  - the operators that handle the container once it has reached the port
  - the port of origin
  - the weather and sea state along the ships voyage
- the current methodology of predicting container claims and the accuracy thereof
- the current information gathering and collating procedures
- the error rates of equipment and personnel operating them

The full list of survey questions is included in Appendix C.

3.1.4.1. Feature Importances

The various features captured in the survey were collated and were assigned relative importances per the indication of such in the survey. Since the survey captured features on a scale of "not at all relevant" to "very relevant" and as having "strong" or "weak" "positive" or "negative" correlation to container damage claims, the importance of each feature, relative to the other features were defined as shown in Tab. 3.1.

Table 3.1.: Feature Importances

Feature	**Importance of Feature**
Identity of Customer	1
Commercial value of the cargo in the container	3
Port of origin	1

Shipping Line	2
Weather at port of origin	1
Weather and sea state along the ship's voyage	1
Fragility of the cargo in the container	0.01
Shipping container's packing season	1
Shipping container's loading season	1
The amount of time the shipping container spends in the container yard	1
The presence of hazardous material in the shipping container	3
The trucking company that moved the container from the port to the customer	1
The presence of sensitive cargo	3
The presence of perishable cargo	3
The presence of high value cargo	2
The weight of the cargo in the shipping container	0.01
The deviation of the center of gravity of the packed container from the geometric center of the container's base	3
The identity of the quay crane operator	1

3.1.5. Vessel Departure Delay

Scheduled and actual vessel departure times are specifically known to the port and the shipping lines. However, this information is sometimes made publicly available (e.g. [72]). Since historical data is unavailable for scheduled departure times (but is indeed available for actual departure times) scheduled departure times are periodically polled, and correlated against historical data on actual departure times. The difference between these gives the delay in vessel departure from port, as shown in Eq. 3.1.

$$DepartureDelay(M) = ATD(M) - ETD(M) \tag{3.1}$$

Where

M is the MMSI of the vessel.

$ATD(M)$ is the actual departure time of the vessel with MMSI M, reported as seconds from epoch.

$ETD(M)$ is the scheduled departure time of the vessel of the vessel with MMSI M, reported as seconds from epoch.

3.1.6. Vessel Service

Given known vessel tracks (as described in Sec. 3.2.2), the methodology of mining real-world vessel service at port is described in this section.

First, instances of a vessel's visit to port are detected. Typically this would be accomplished by identifying the port's latitude and longitude coordinates and identifying segments of the vessel's track with a reported speed of 0 knots and a minimal distance between the vessel and port. However, due to errors in the GPS signal and map projection, this method proves to be too noisy to yield useful data. Therefore, the coastline along which the port is located is modeled as a series of line segments, whose end-points are specified as latitude-longitude geospatial coordinates.

Next, stationary segments of the vessel's track are detected - these are contiguous subsequences of time-sorted AIS contacts from the vessel that report a speed of 0.5 knots or lower [73]. These segments are then filtered based on geospatial distance from port, so that segments describing stationery vessels in open waters are appropriately excluded from the analysis.

The first contact of a segment is the actual arrival time of the vessel at port, while the last contact of the segment describes its actual departure time. The difference between the two is the calculated vessel service time (as shown in Eq. 3.2 and illustrated in Fig. 3.2).

The Maritime Mobile Service Identity (MMSI) of each of these vessels can then be correlated against historically available AIS messages which report the draught of the vessel, along with its physical dimensions (length and width). This is used to calculate the volume of water displaced (as seen in Eq. 3.3 and Eq. 3.4), which when multiplied by the density of water gives the mass of displaced water (as seen in Eq. 3.5). This is the total mass of the vessel including fuel, crew, and the mass of the shipping containers on board. Assuming that the remaining weights are negligible in the absence of more specific information (or otherwise allowing for such values within a margin of error), the mass of the displaced water is the combined mass of the shipping containers on board the vessel. The number of shipping containers on board (given the draught and physical dimensions of a vessel) is therefore computed by dividing the mass of displaced water by the average mass of a shipping container (as seen in Eq. 3.6). Yet, since some vessels may be loaded with heavier containers than others on average, the average mass of a shipping container is drawn from a normal distribution with μ =75 tons and σ =10 tons [1], capturing the range of weights of a loaded shipping container.

$$ServiceTime(M) = ATD(M) - ATA(M) \tag{3.2}$$

Where

M is the MMSI of the vessel.

$ATD(M)$ is the actual departure time of the vessel with MMSI M, reported as seconds from epoch.

$ATA(M)$ is the actual arrival time of the vessel of the vessel with MMSI M, reported as seconds from epoch.

$ServiceTime(M)$ is the service time of the vessel with MMSI M, reported as seconds.

$$totalDraught(v) = d_o(v) + d_i(v) \tag{3.3}$$

$$volume_{water} = totalDraught(v) \times L(v) \times W(v) \tag{3.4}$$

$$mass_{water} = V_{water} \times D_{water} \tag{3.5}$$

$$numContainers = \frac{mass_{water}}{\mathcal{N}(\mu = 75, \sigma = 10)} \tag{3.6}$$

Where

$d_i(v)$ is the draught (in meters) of vessel v as it enters the port

$d_o(v)$ is the draught (in meters) of vessel v as it exits the port

$L(v)$ is the length (in meters) of vessel v as reported in AIS messages

$W(v)$ is the width (in meters) of vessel v as reported in AIS messages

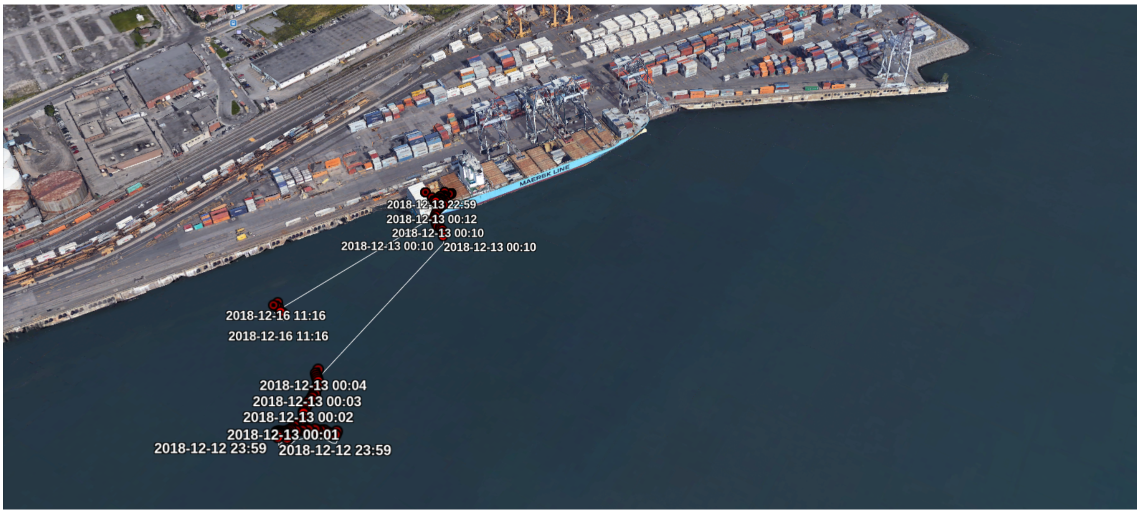


Figure 3.2.: An Example Vessel Service Track

D_{water} is the density of water (1000Kg/m^3)

Finally, the real-world resource deployment is mined in order to benchmark the performance of this optimization against established practices in the real world. Since the given start and end times of each vessel service from the publicly available schedule are only estimates, the actual start and end times of each vessel service are mined by computing the time at which the vessel arrives at a berth and the time at which it departs from the berth. As previously described, the draught measures and other AIS values give the total number of containers processed during this vessel's service period. In the absence of additional data, it is assumed that the rate of processing containers remains approximately constant throughout the vessel's service period. Therefore, dividing the number of processed containers by the time period of the service window yields the number of containers processed per eight-hour shift in the service window. Given that a single crane can load or unload a single container from a vessel requires two minutes [6], the total resource deployment is computed as the number of individual cranes required to process the computed number of shipping containers over all vessels being serviced. Note that this must be computed per eight-hour shift, in order to capture the notion that personnel may be scheduled to work in an integer number of eight hour shifts.

3.1.7. Summary

Data was collected from CBSA, AIS messages, NOAA, and such sources. This data was then processed to be a part of the dataset used in the analyses presented in this thesis proposal. Certain additional data could not be captured from publicly available sources and needed to be synthesized per the specifications outlined in the data captured by the survey of industry experts (see Sec. 3.1.4). The methodologies used to synthesize this data are explained in detail in Sec. 3.2.

3.2. DataSet Synthesis

Datasets were created in order to perform the necessary experiments. However, since some data was not available from real-world sources, they needed to be synthesized. The synthesis of such data is discussed in this section.

3.2.1. Container Damage Feature Weights

Based on the results from the survey of Canadian domain experts (discussed in Sec. 3.3), values of shipping container features, necessary to make insurance claims prediction were synthesized. These attributes and the synthesis of their values are discussed in this section. Each feature was assigned a value drawn from a specific distribution, weighted by the strength of the correlation indicated in the survey results. The sum of these weighted values comprises a damage value, which informs whether the shipping container was claimed for damages. The weights of the different features are shown in Tab. 3.2.

Feature	Weight
Weather and Sea State	1
Shipping Line	3
Container Weight	0.01
Commercial Cargo Value	3
Cargo Fragility	0.01
Cargo Sensitivity	3
Container Weight Balance	3
Quay Crane Operator	1
Container Packing Season	1
Container Loading Season	1
Customer Identity	1
Logistics Company	1
Time in Storage Yard	1

Table 3.2.: Weights of Features

3.2.2. Shipping Tracks

Each shipping container in this dataset was randomly assigned to be on one of forty six known vessel voyage tracks. These tracks were computed by correlating AIS contact data to form several distinct tracks. These tracks were then filtered to exclude vessels whose voyages either did not end at a Canadian port or did not originate in some port. The remaining tracks varied widely in their inter-contact time, i.e. the amount of time between two subsequent contacts. Several tracks had short bursts of AIS reports with long periods of time in between these bursts. Other tracks had consistently frequent AIS reports, which allow for more consistent analysis. Of these, tracks with a reporting frequency lower than two minutes (i.e. the time between two subsequent contacts was over two minutes) were filtered out. This is because a lack of geospatial and temporal information on a vessel would decrease the veracity of any analysis on environmental effects of a vessel's voyage on the shipping containers it carried. Forty six tracks remained at the end of the

[1] Maritime Mobile Service Identity (MMSI) is a unique identifier for a ship

filtering (varying from $10,000$ to 2.5M contacts)[2], which were ultimately used in this study. These tracks include voyages of vessels in the Period of Interest (POI) between January and March, 2014.

3.2.3. Weather and Sea State

The weather and sea state information was freely available from NOAA's website. The data contains hourly forecasts (and historical data) for grid points spaced 0.5° latitude/longitude apart. Thus, the resolution of the data is shown in Tab. 3.3. With this information, it is possible to query the exact weather and sea state conditions along a ship's voyage. The sea state was computed from the wave height data in the NOAA dataset. Each reported wave height reading was then measured on the Douglas Sea Scale (DSS) (seen in Tab. 3.4 [5]).

Dimension	**Resolution**
Temporal	1 hour
Spatial - latitude	0.5°
Spatial - longituthe de	0.5°

Table 3.3.: Data Resolution

The effect of the DSS measure on shipping container damage is computed as $\frac{1}{2\times(1+e^{7-x})}$, where x is the DSS measure.

3.2.4. Shipping Lines

Each container was assigned to be transported by a vessel on a voyage as described in Sec. 3.2.2. However, the shipping lines that operate these vessels is an attribute of the dataset that is not captured in that information. In order to determine the shipping line responsible for transporting a given shipping container, the Global Top

[2] the dataset contained over 100 tracks prior to filtering

Douglas Sea Scale Measure	Wave Height Range (m)	Description
0	No Wave	Calm (glassy)
1	0.0 - 0.10	Calm (rippled)
2	0.10 - 0.50	Smooth
3	0.10 - 1.25	Slight
4	1.25 - 2.50	Moderate
5	2.50 - 4.00	Rough
6	4.00 - 6.00	Very rough
7	6.00 - 9.00	High
8	9.00 - 14.00	Very High
9	Over 14.00	Phenomenal

Table 3.4.: Douglas Sea Scale[5]

100 Shipping Lines by annual cargo throughput [74] during the POI is considered. Each shipping container is probabilistically assigned to one of these shipping lines using a roulette wheel selection scheme (based on each shipping line's annual cargo throughput). The probabilistic selection is performed by means of a biased roulette wheel [75], in which each section of the wheel corresponds to a shipping line and is proportionally as large as the fraction of that shipping line's annual cargo throughput of the global annual cargo throughput. The probability that a given shipping line would cause an error (which would in turn cause shipping container damage) was modeled as a function of its relative fleet size, relative annual throughput, and relative market share, as shown in Eq. 3.7.

$$P(Error) = \begin{cases} 0 & c > \frac{2}{3}C \\ 0.5 & c < \frac{1}{3}C \\ \frac{3c-1}{2} & \text{otherwise} \end{cases} \tag{3.7}$$

Where

$c(S) = 0.3 \times fleetSize(S) + 0.35 \times annualThroughput(S) + 0.35 \times marketShare(S)$

S is a given shipping line

$C = max(\{c(S) | S \in ShippingLines\})$

3.2.5. Container Weight Distribution

Each container was assigned to be of a random weight drawn from a distribution described by Eq. 3.8, visualized in Fig. 3.3. The chosen numbers (namely, 55 and 110) correspond to the cargo weight capacities (in metric tons) of standard forty-foot shipping containers and Twenty-foot Equivalent Units (TEUs)[3].

$$w = \begin{cases} 55 & \text{with probability } 0.2 \\ 275x_{0.2 \leq x \leq 0.4} & \text{with probability } 0.2 \\ 110 & \text{with probability } 0.6 \end{cases} \tag{3.8}$$

Further, given the weight of a container, the probability of damage-causing error was modeled as shown in Eq. 3.9.

$$P(Error|w) = 2 \times \left(\frac{w}{110} - 0.25\right)^2 \tag{3.9}$$

3.2.6. Commercial Value of Cargo

The commercial value of the cargo in a shipping container was modeled from publicly available data from CBSA's website [76]. This was therefore modeled as a Gausssian

[3]An empty container weighs 55 tons, and can be packed to a total weight of 110 tons

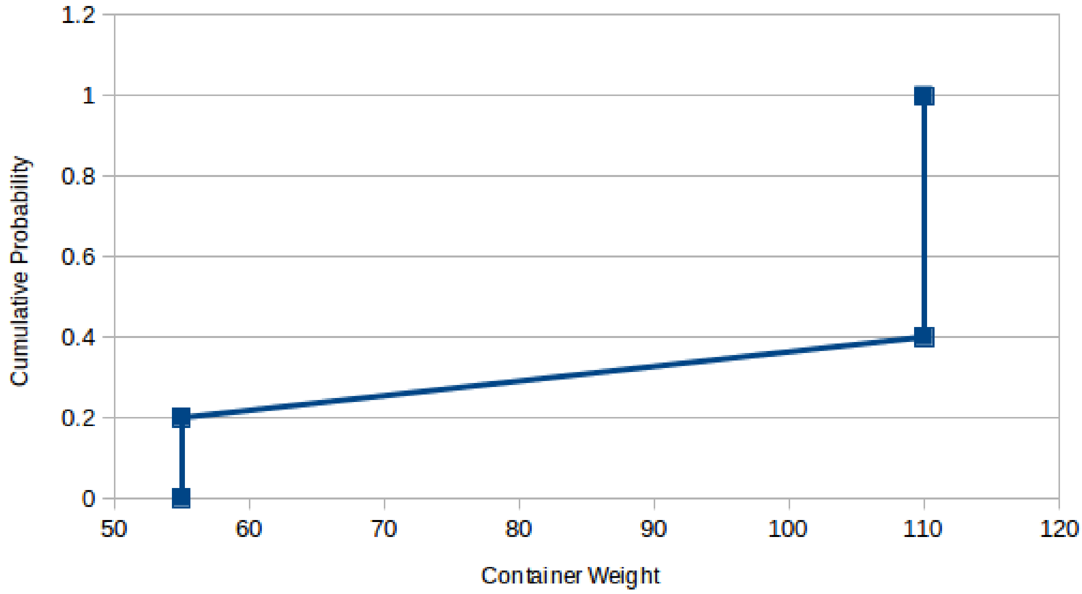


Figure 3.3.: Shipping Container Weight Distribution

distribution with $\mu = \frac{10^5}{2}$ and $\sigma = \sqrt{10^{10}}$. While it is valid to think of this value as being positively correlated with cargo weight, it is not necessarily the case, as cases of lighter and more expensive materials do exist. As a result, it is impossible to correlate the two, making them indeed independent distributions.

Given the commercial value of the cargo inside a shipping container ($v \in [0, V]$), the probability of damage-causing error was modeled as shown in Eq. 3.10.

$$P(Error|v) = \begin{cases} 0 & v \leq \frac{V}{3} \\ 0.5 & v \geq \frac{V}{3} \\ 0.5 \times \frac{v}{V} - 0.5 & \text{otherwise} \end{cases} \tag{3.10}$$

3.2.7. Cargo Fragility and Sensitivity

Cargo fragility refers to whether the cargo is marked as being fragile. This is therefore implemented as a binary flag, drawn from a uniform distribution over $[0, 1]$. Cargo sensitivity is reported by the consignor or customer. From the surveys, it is known that shipping containers with sensitive cargo have a higher likelihood of being claimed in the event of container damage. As a result, this attribute was included in the dataset and was also modeled as a binary flag drawn from a uniform distribution over $[0, 1]$.

The probability of damage-causing errors given the fragility and the sensitivity of the cargo within a given shipping container are shown respectively in Eq. 3.11 and Eq. 3.12.

$$P(Error|f) = 0.01 \times f \tag{3.11}$$

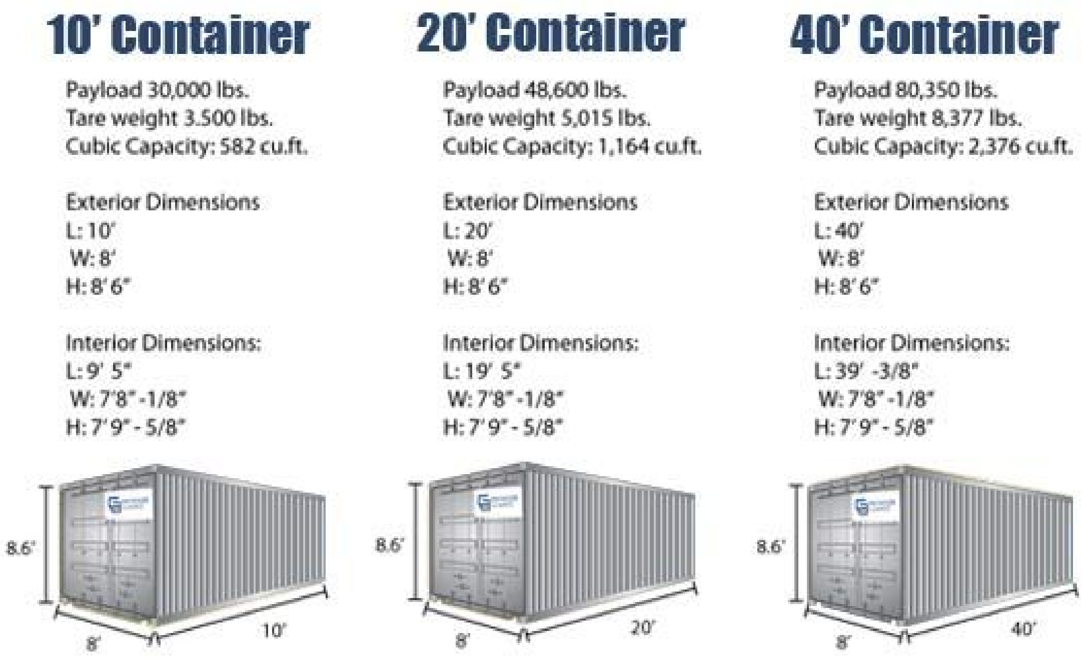
$$P(Error|s) = 0.5 \times s \tag{3.12}$$

3.2.8. Container Weight Balance

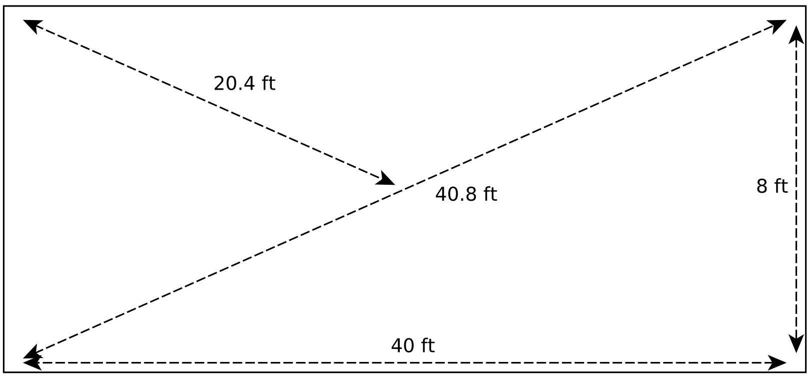
The weight balance of a shipping container was modeled as the linear distance between the center of mass projected onto the container's base (as seen in Fig. 3.4), and the geometric center of the container's base. Given that the dataset contains data describing 40ft containers, this distance is limited to half the length of the diagonal of the base of the shipping container, namely 20.4ft.

The probability of damage-causing errors given the weight balance of a shipping container is shown in Eq. 3.13.

$$P(Error|d) = 0.5 \times \frac{d}{20.4} \tag{3.13}$$



(a) Shipping Container Dimensions [77]



(b) Weight Balance Calculation on Container's Base

Figure 3.4.: Container Weight Balance

This value is considered agnostic of the nature of the cargo within the container. Oddly shaped cargo or cargo with otherwise non-uniform mass distribution directly affect the container weight balance, which is described by this feature, without considering the specifics of the contained cargo. However, non-solid cargo (such liquid or dry bulk) are out of the scope of this study and a left as future work.

3.2.9. Quay Crane Operator

The identity of the quay crane operator who unloaded a given container from the vessel carrying it onto an intra-port truck was drawn from a uniform distribution over a pool of available operators.

3.2.10. Packing and Loading Season

In order to capture the effects of seasonal changes on container damage, the season in which a container was packed (and/or loaded) was drawn uniformly at random from the set {summer, winter, spring, fall}. The probability of damage-causing errors given the packing and loading season of a container were each set to 0.5 (and 0 otherwise) if the container was packed or loaded in the fall or spring seasons.

3.2.11. Customer Identity

The customer is defined as the person or organization to whom the shipping container will be ultimately deposited. In order to capture the notion that some customers are more litigious than others, the customer's identity was drawn from a random uniform distribution. The probability of a claim being filed by a given customer was drawn from a uniform distribution over $[0, 0.5]$, and the claim amount was drawn from a uniform distribution over $[0, 10^8]$.

3.2.12. Logistics Company

Each container was assigned to be transported by a truck from a logistics company with a fleet of terrestrial trucks. In order to determine the trucking company responsible for transporting a given shipping container, the Global Top 100 trucking companies by annual cargo throughput [78] during the POI is considered. Each shipping container is then probabilistically assigned to one of these trucking companies using a roulette wheel selection scheme (based on each shipping line's annual cargo throughput). The probabilistic selection is performed by means of a biased roulette wheel [75], in which each section of the wheel corresponds to a trucking company and is proportionally as large as the fraction of that shipping line's annual cargo throughput of the global annual cargo throughput.

The probability that a given logistics company would cause an error (which would in turn cause shipping container damage) was modeled as a function of its relative fleet size, relative annual throughput, and relative age, as shown in Eq. 3.14.

$$P(Error) = \begin{cases} 0 & c > \frac{2}{3}C \\ 0.5 & c < \frac{1}{3}C \\ \frac{3c-1}{2} & \text{otherwise} \end{cases} \tag{3.14}$$

Where:

$c(t) \; = 0.3 \times fleetSize(t) + 0.35 \times annualThroughput(t) + 0.35 \times age(t)$

t is a given logistics company

$C \; = max(\{c(t)|t \in logisticsCompanies\})$

3.2.13. Time in Storage Yard

After being unloaded at the destination port, a shipping container is stored in the storage yard at that port before it is picked up by a truck for final delivery to the customer. As a result, the amount of time a shipping container spends in the storage yard is a recorded feature of this dataset, drawn uniformly at random from $[0, 364]$ days. The lower limit of 0 captures the notion that shipping containers are sometimes dispatched from the port on the day that they are received. The upper limit of 364 captures the notion that shipping containers are not stored in a storage yard for a period of time exceeding one year. Given the duration over which a shipping container is stored in a port's storage yard, the probability of damage-causing error is shown in Eq. 3.15.

$$P(Error|t) = \frac{366}{365 - t} \tag{3.15}$$

3.2.14. Port Situation Reports

Ports write daily situation reports (an example of this is seen in [79]). Since such reports are extremely sensitive to the port and are not publicly available, similar reports were manually synthesized for use in this study (examples of the relevant sections of such synthetic reports are listed in Tab. 3.5, and an example situation report is seen in Tab. 3.6). As seen in this example, the situation report contains the name of the inbound vessel, a unique identifier for its visit to port, its list of port calls to subsquent ports, the last visited port, the vessel's current geolocation, its arrival schedule to this port, and the immediately subsequent ports for it to visit. The final column contains notes pertaining to any delays this vessel may face, which is of particular importance to this study. Mining these notes provide insights into the expected delays at ports, which can be used to optimize port-side resource deployment.

From the example report [79], it is evident that reports of any foreseeable delays in port operations are only present when such a delay is expected. When no delay is expected, these reports are left empty. The specifics of the usage of these synthetic reports are discussed in Sec. 3.6.2.

The current resource deployment is known at any given time. The difference in time between the the given moment and the start of the current shift is trivially computed, and computing the number of two minute intervals in this period gives the number of containers processed thus far in this shift. While this calculation yields the number of remaining containers to be processed, the incoming vessel schedule provides another source of shipping containers to be processed. Adding the data from these two streams together yields the size of the backlog (i.e. the number of remaining containers to be processed) at any given time. An increase in the size of this backlog at the end of a given day indicates impending vessel service delay, a the situation report is synthesized to include a comment indicative thereof. On the other hand, if the backlog decreases, the comment section is left empty.

It is therefore clear that situation reports must be generated adaptively, in response to the current backlog, which is dictated by the current resource deployment; which in turn is dictated by the optimizer (explained in Sec. 3.6). Therefore, the generation of these situation reports occurs as part of the fitness evaluation function of the multi-objective evolutionary algorithm (described in Sec. 3.6.2) in response to the size of the current backlog at the end of each simulated day). Further, as discussed in Sec. 3.6.2, these situation reports are ingested as soft data in order to optimize resource deployment.

Example Situation Report
extreme delay due to weather
delay due to unavailable port-side resources
congestion-induced delay
inbound delay due to weather
service delays caused outbound delay

Table 3.5.: Examples of Synthetic Situation Reports

3.2.15. Summary

The methodologies used to synthesize unavailable data are discussed in this section. These data are typically known to real-world stakeholders, but are unavailable for an academic study. As a result, a survey was used to capture the characteristics of the distributions of the values of these features (see Sec. 3.1.4), based on which synthetic data was created to complete an otherwise feature-incomplete dataset.

VESSEL	CODE / VOY	ROTATION	LAST PORT	CURRENT POSITION	ETA NEXT PORT	FORWARD SCHEDULE	COMMENTS
Imua II	IMA 057	AKL-LTK-SUV-APW-PPG-RAR-AIT-VAV-TBU-AKL Auckland,Lautoka,Suva,Apia,Pago,Rarotonga,Aitutaki,Vavau,Nukualofa,Auckland	APW ARR 07:18, 08 Aug SLD 13:42, 08 Aug	PPG ARR 10:12, 08 Aug Lt ETD 14:00, 08 Aug Lt	RAR ETA 06:00, 11 Aug Lt	AIT 14 Aug Lt	
Liloa II	LL2 023	AKL-LTK-SUV-APW-PPG-RAR-AIT-NIU-TBU-AKL Auckland,Lautoka,Suva,Apia,Pago Pago,Rarotonga, Aitutaki, Niue, Nuku'alofa, Auckland	TBU ARR 02:24, 06 Aug SLD 08:24, 06 Aug	AT SEA	AKL ETA 12:00, 10 Aug	LTK 15 Aug SUV 16 Aug	Delay Nukualofa to Auckland with bad weather.

Table 3.6.: Examples of Real-world Situation Reports

3.3. Prediction of Container Damage Insurance Claims for Optimized Maritime Port Operations [1]

Commercial maritime ports require the optimization of highly involved workflows, which are typically induced by the incidence of an insurance claim on a damaged shipping container. These workflows involve data gathering and collation from multiple sources, and filtering this data based on relevance to the specific incident [80, 81]. Thus, the process includes:

- visual inspection logs from the quay crane operators (who unloaded the shipping container from the ship)
- visual inspection logs from various checkers in the container yard
- cargo manifests that describe properties such as commercial value and fragility of the cargo
- surveillance camera footage from throughout the port
- weather data (e.g. visibility, precipitation, wind speed, sea state, etc) pertaining to the route traveled by the ship while inbound to the port

Once processed, the information extracted form this data is used to determine the point of incidence of the damage, which in turn advises port officials whether the insurance claim should be disputed, settled, or redirected to a third party responsible for the damage [82, 83, 84]. While data gathering and collation are fairly fast and accurate, they do entail a high computational burden due to the computational costs associated with processing noisy, inaccurate, and often incomplete data (such as personnel logs, etc). This motivates the need to predict shipping container damage and insurance claims to narrow the subset of shipping containers for which to collect and process data. This data may then be presented to port officials upon the incidence of an insurance claim on a specific shipping container.

Data collection and processing aside, the human expert predictions are known to be erroneous. A study of the effects of prediction specificity on prediction accuracy in sports bets showed that both experts and novices have higher prediction accuracy when making general predictions (in the form of predicting the winning team in a soccer match) rather than very specific predictions (in the form of predicting the final score of the soccer match). This effect was statistically significant even when the experiment was controlled for gambling rewards (such as monetary rewards for correct prediction) [85]. This effect is not necessarily due to the increase in the number of alternative prediction outcomes, but also has causes rooted in human cognitive biases which narrow focus onto a subset of facts, detracting from a more preferred, holistic consideration of all available information[86]. This problem is further exacerbated when the predictions are to be made on longer-duration time series data [86]. Additionally, human experts are often swayed by risk aversive tendencies and confirmation bias, which negatively impacts their prediction accuracy [85, 87]. Finally, a NASA study shows that an increase in the number of simultaneous predictions decreases the accuracy of each prediction [81].

A survey was conducted to capture some of the domain-specific expertise in the industry. This survey captured aspects of commercial maritime port operations including:

- correlations between container damage claims and
  - the consignor
  - the customer
  - the shipping line

  - the operator discharging the inbound ship
  - the operators that handle the container once it has reached the port
  - the port of origin
  - the weather and sea state along the ships voyage
- the current methodology of predicting container claims and the accuracy thereof
- the current information gathering and collating procedures
- the error rates of equipment and personnel operating them

The survey was designed to ask experts how strongly each attribute correlated with shipping container damage, as well as the direction of correlation. The results of the survey are shown in Tab. 3.7.

Feature	**Correlation to Shipping Container Damage Claims**
Weather and sea state	Positive correlation
Characteristics of Shipping Line	High positive correlation
Shipping container weight	Low positive correlation
Commercial cargo value	High positive correlation
Cargo fragility	Low positive correlation
Presence of sensitive cargo	High positive correlation
Container weight imbalance	High positive correlation
Quay crane operator	Positive correlation
Container packing season	Positive correlation
Container loading season	Positive correlation
Customer identity	Positive correlation
Characteristics of trucking company	Positive correlation
Time spent in storage yard	Positive correlation

Table 3.7.: Feature Correlations to Container Damage Claims

3.4. Improving Container Damage Claims Classifier Performance Veracity with Leave One Batch Out Training

While presenting [1], a concern was raised that since the size of the dataset is much larger than 46 (the number of known shipping tracks in the dataset), the machine learning algorithms likely did not use the weather features along a vessel's voyage at sea as learned parameters, giving them an undue advantage and inflating their performance values. This inflation of a classifier's MOE lowers its MOPs, which ultimately leads to poorer performance and generalization in the long term. In order to address this concern, three experiments were designed and are presented in this section.

3.4.1. Removing Weather Features from the Dataset

The experiments in [1] were rerun, but with the weather features removed from the dataset. If the results from these new experiments are significantly worse (as indicated by lower MOPs) than those in [1], it would indicate that the results in [1] were indeed biased and that further experiments need to be performed to correct for this bias. However, these worse classifiers would indeed have higher MOEs as they would be performing the required interpolation of weather features, as opposed to some bias-inducing memorization. This can be described as a lack of resilience in the face of lower dimensional data features, which describes a lower MOE [21]. The performance of various classifiers in this dataset are shown in Tab. A.2.

3.4.2. Using a Validation Batch

The dataset used in [1] contains 23 features, 9 of which pertain to weather and sea state along the voyage of a vessel carrying a given shipping container. Using the vector of these nine features as a signature, all shipping containers in the dataset can be grouped by their signature. One group is held out in accordance with a Leave One Batch Out (LOBO) learning methodology, while 10x10 fold cross validation is performed on the remainder of the dataset, comprised of the individual records from all other batches (this process is visualized in Fig. 3.5). All the experiments in [1] were then performed under this experimental methodology.

A statistically significantly worse performance under this methodology as compared to [1] (lower MOPs, regardless of the difference in MOEs) would suggest that further study is required.

The performance of various classifiers with this LOBO methodology are shown in Tab. A.3 and a combined graph showing the relative performances across all datasets is shown in Fig. 3.7.

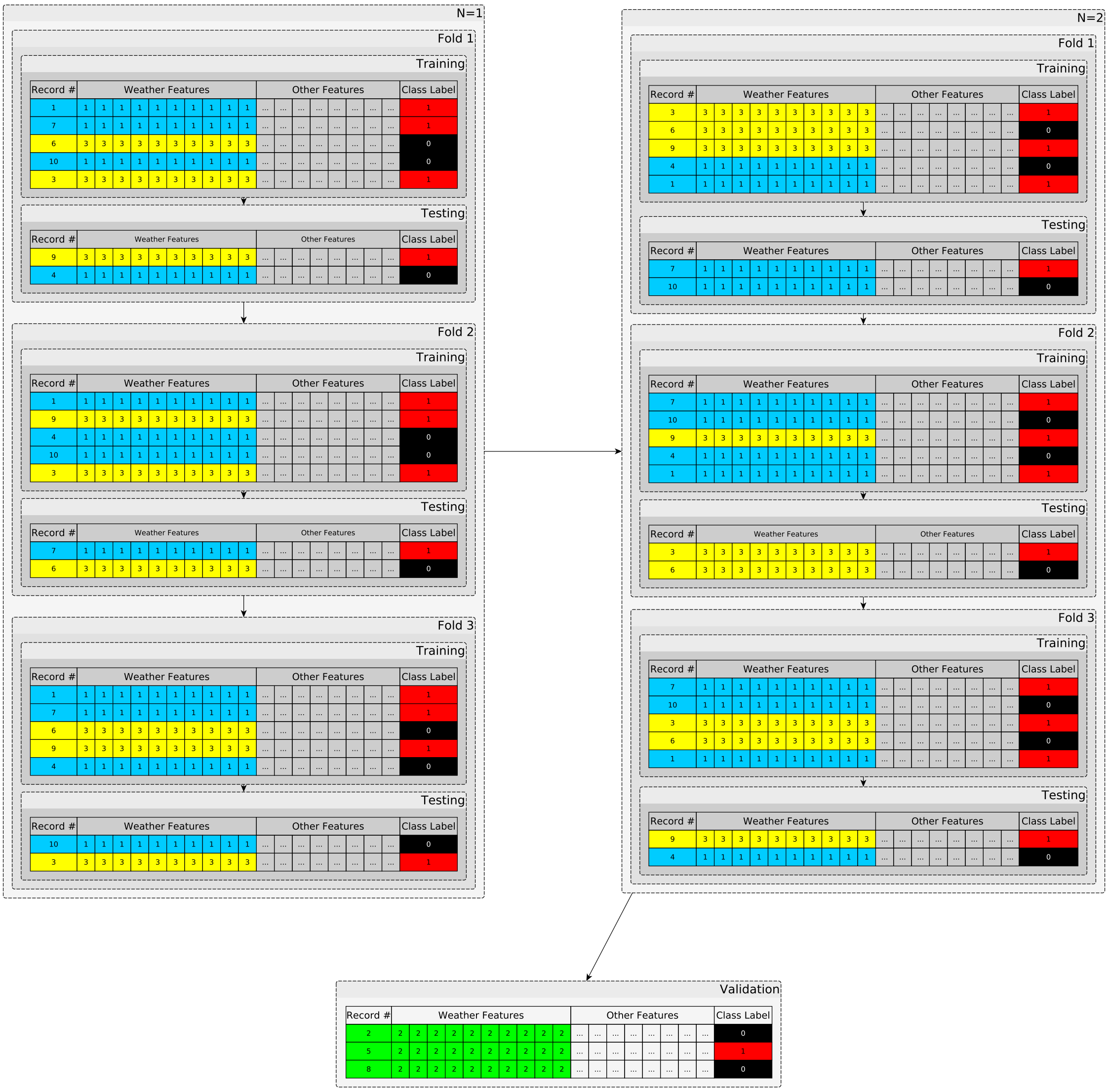


Figure 3.5.: Using a Validation Batch

3.4.3. Cross Validation with LOBO

Similar to the methodology in Sec. 3.4.2, the records in the dataset are partitioned into batches by the signatures of their weather and sea state values. In each iteration of the 10x10 fold cross validation, one batch is left out for testing. Finally, the machine learning model is tested for performance on a batch that was previously held out and never used in training. This process is illustrated in Fig. 3.6.

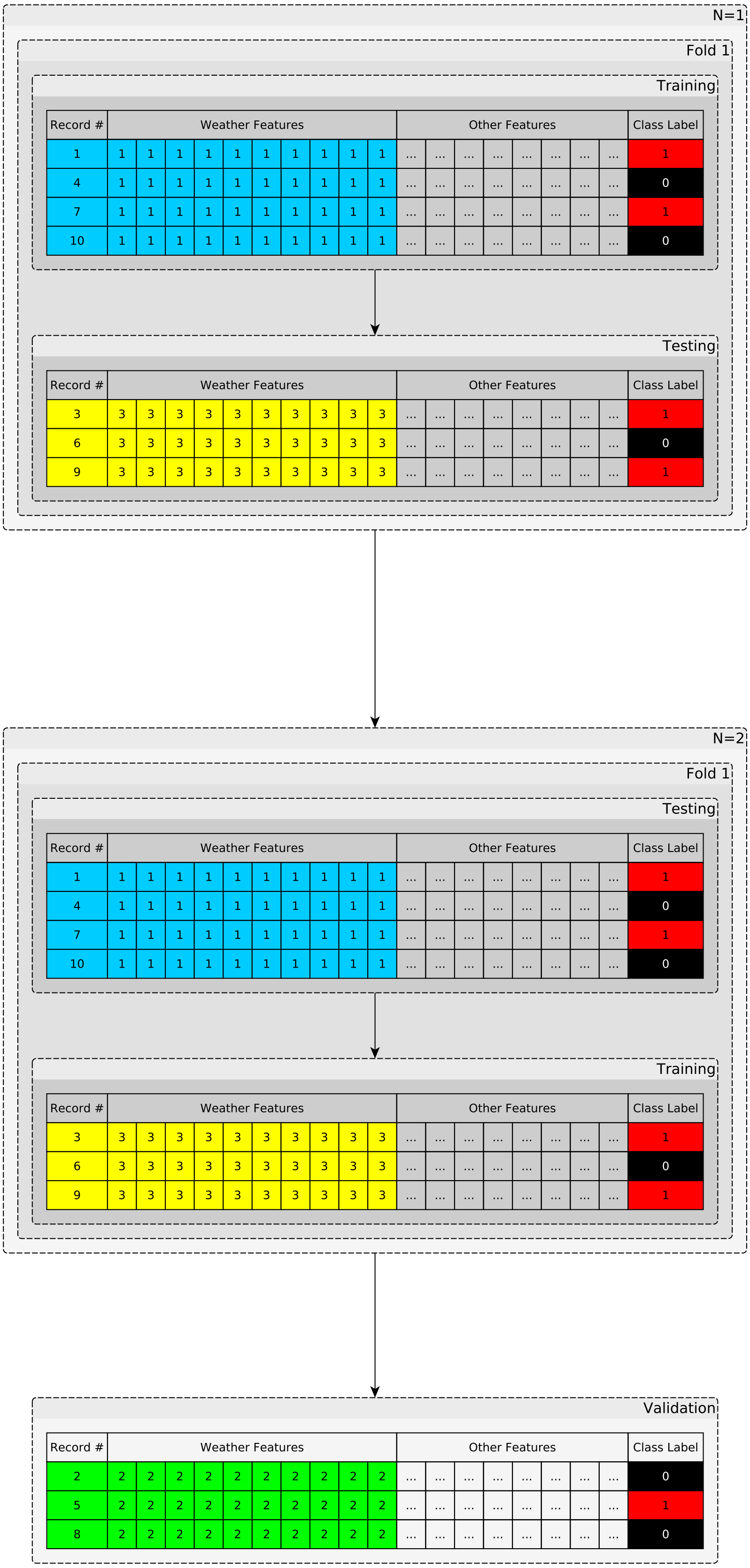
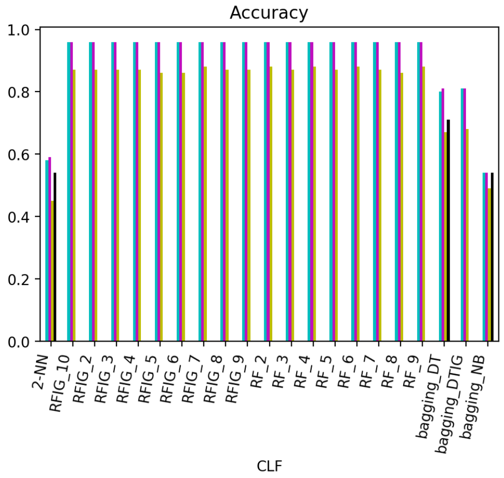
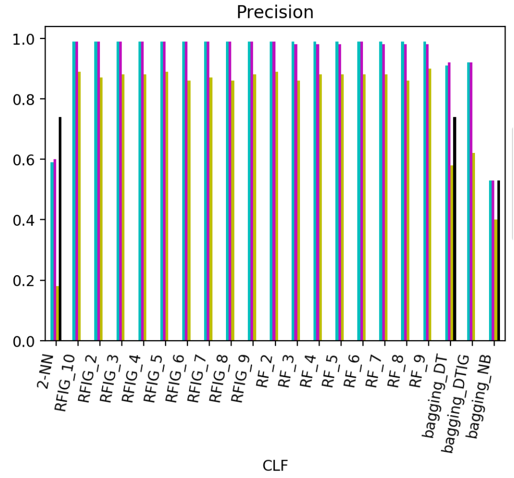


Figure 3.6.: Cross-Validation with LOBO

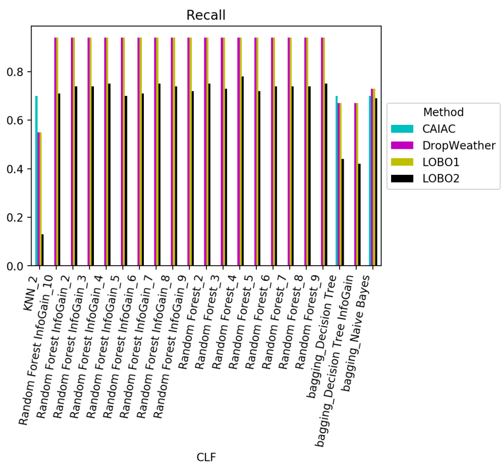
The performance of various classifiers with this LOBO methodology are shown in Tab. A.4. A combined graph showing the relative performances across all datasets is shown in Fig. 3.7.



(a) Accuracy



(b) Precision



(c) Recall

Figure 3.7.: Relative Performance across Drop-Weather, LOBO, and Cross Validation with LOBO

3.4.4. Conclusions

From the results presented in Sec. 3.4.1, Sec. 3.4.2, Sec. 3.4.3, it is evident that performing the classification without the weather features yields better classifier performance than when the weather features are included during classification. This is counter to the expectations outlined at the outset. This could potentially be explained by the dataset synthesis methodology (see Sec. 3.2); specifically, the non-weather features are drawn from simple distributions that are easily learned by machine learning algorithms. Therefore, these results do not adequately address the concern of learning bias requiring further analysis.

Following up the inconclusive analysis in Sec. 3.4.1, the dataset is partitioned based on the values of the weather features (as described in Sec. 3.4.2). One such partition is held out as a validation set, while training and testing are performed on the remainder of the dataset. The results from these experiments (shown in Tab. A.3) show that the classifiers outperform their counterparts in Sec. 3.4.1. This suggests that this cross-validated training method is superior to training method and warrants more investigation for a new publication as it promises better generalization.

Given the performance increase noted in Tab. A.3, the extension of that methodology (used in Sec. 3.4.3) promises better results. However, since this observed to not be the case (see Tab. A.4), concluding that the former training methodology affords better generalizability than the latter. This is especially relevant to information fusion effectiveness as these experiments have been performed with data restricted to a three month POI (and therefore, limited variance in weather patterns across the dataset). Performing these experiments against a larger data set with a one-year POI will reconfirm the conclusions about the generalizability of LOBO methodology.

Yet, the argument still holds that the superior performance of using a validation batch over performing cross-validation with LOBO could be an artifact of the restricted POI of the dataset which captures only a subset of annual weather patterns. Unfortunately, since no other maritime voyage track data is available, this criticism cannot be further investigated at the moment. However, negotiations are currently under way to acquire such data from data vendors to make this investigation possible.

3.5. Improving Container Damage Claims Classifier Performance with Metalearning

As an extension of the work in [1], the performance of the ML methodologies applied to this problem can be further improved by the use of metalearning techniques from Level 4 of the JDL/DFIG Data Fusion model.

Metalearning allows for the learning of correlations between feature vectors and the performance of various classifiers [88]. This allows for the optimal classifier selection on unseen records, the methodology for which is explored in this section. Random forest regressors were used to learn this relationship between data features and the classifier performance. Their use was motivated by the performance of tree-based classifiers in the prediction task. Further, since these regressors performed sufficiently well, no further metalearners were evaluated as part of this study.

3.5.1. Dataset Generation

The dataset used in Sec. 3.4 is used as the base dataset for this study. The metalearning dataset is created by determining a spanning set of jointly performant ML algorithms and computing their relative performances. First, each record in the existing dataset is augmented with a number of columns - one for each classifier used in [1]. Next, the corresponding column was marked with a binary performance indicator, denoting whether each classifier was able to correctly classify the given record, forming a k-hot encoding [89, 90, 91] of the classifier's per-record performance. These augmented records are then grouped by their feature vectors (i.e. all data columns with the exception of those comprising the k-hot encoding scheme), and the resultant performance indicators for each classifier were summed over all records in the group. An illustrative example of this is shown in Fig. 3.8.

Figure 3.8.: Augmenting the Original Dataset (with a set F of features and a set C of classifiers) for Algorithm Selection

Record #	f_1	f_2	...	$f_{\|F\|}$
1	1	0	1	1
2	1	0	1	1
3	0	1	0	0
4	0	1	0	0
5	1	0	1	0

(a) Original Dataset of Metafeatures

Record #	f_1	f_2	...	$f_{\|F\|}$	c_1	c_2	...	$c_{\|C\|}$
1	1	0	1	1	1	1	...	0
2	1	0	1	1	0	1	...	0
3	0	1	0	0	0	0	...	0
4	0	1	0	0	0	1	...	1
5	1	0	1	0	0	0	...	1

(b) Per-Record k-hot Classifier Performance

Record #s	f_1	f_2	...	$f_{\|F\|}$	c_1	c_2	...	$c_{\|C\|}$
1,2	1	0	1	1	1	2	...	0
3,4	0	1	0	0	0	1	...	1
5	1	0	1	0	0	0	...	1

(c) Grouped Dataset for Algorithm Selection

The metadataset is then computed, in which each record contains all the features of the original dataset, and the fraction of correct predictions per classifier. This is seen in Fig. 3.9. Note that there is one fewer record in the metadaset than in the original dataset as the original dataset contains two distinct rows with identical metafeature vectors. Since `Classifier1` correctly predicted one out of these two instances, it has a value of $\frac{1}{2} = 0.5$ in the metadataset. Similarly, since `Classifier2` incorrectly predicted both instances, it has a value of 0 in the metadataset. Since it is known that no one classifier performs at 100% accuracy across the entire dataset, the next step is to determine the classifier with the highest likelihood of correct prediction based on the metadataset. That classifier is then used to classify the new unseen data record. While this comes with a small MOE decrease in that predictions on new data will require an additional step, it is likely to improve overall MOEs in increased accuracy over all new data.

Figure 3.9.: Determining the Spanning Classfiers from the Grouped Dataset

Record #s	f_1	f_2	...	$f_{\|F\|}$	c_1	c_2	...	$c_{\|C\|}$
1,2	1	0	1	1	1	2	...	0
3,4	0	1	0	0	0	1	...	1
5	1	0	1	0	0	0	...	1

(a) Grouped Dataset for Algorithm Selection

Record #s	c_1	c_2	...	$c_{\|C\|}$
1,2	2	1	...	4
3,4	4	2	...	3
5	4	3	...	1
Summed Ranks	10	6	...	8

(b) Computing Ranks from the Grouped Dataset

Record #s	c_1		...	$c_{\|C\|}$
Removed				
3,4	4		...	3
5	4		...	1
Summed Ranks	10		...	8

(c) Removing c_2 and Relevant Groups from the Grouped Dataset

This process yields four classifiers, namely:

1. Adaboosted Decision Trees with the Information Gain impurity measure
2. Adaboosted Decision Trees with the $\sqrt{Gini}$ impurity measure
3. Bagging Decision Trees with the $\sqrt{Gini}$ impurity measure

4. Random Forests with 15 $\sqrt{Gini}$ decision trees

The representation of these classifiers in the dataset is shown in Tab. 3.8, while the computational complexity of their training times is shown in Tab. 3.9.

Classifier	Percentage of Best Performant Records
AdaBoosted Decision Trees (with the $\sqrt{\text{Gini}}$ impurity measure)	97.09%
AdaBoosted Decision Trees (with the Information Gain impurity measure)	2.79%
Bagging with Decision Trees	0.12%
Random Forests with 15 $\sqrt{\text{Gini}}$ Decision Trees	6.67×10^{-3}%

Table 3.8.: Representation of Classifiers in Algorithm Selection Dataset

Classifier	Training Time Complexity
Decision Trees with the $\sqrt{\text{Gini}}$ impurity measure	$O(F \cdot S\log(S))$ [68]
AdaBoosted Decision Trees (with the $\sqrt{\text{Gini}}$ impurity measure)	$O(F^2 S\log(S))$
AdaBoosted Decision Trees (with the Information Gain impurity measure)	$O(F^2 S\log(S))$
Bagging with Decision Trees	$O(S^2\sqrt{F})$
Random Forests with 15 $\sqrt{\text{Gini}}$ Decision Trees	$O(F \cdot S\log(S))$

Table 3.9.: Training Time Complexity of Classifiers in Algorithm Selection Dataset (where F is the number of features in the dataset and S is the number of samples in the training set)

Finally, we revisit the dataset with the k-hot encoding and compute the posterior probability with which each classifier in the previously identified spanning set of classifiers is likely to correctly classify a record, given its features. The resultant Algorithm Selection dataset includes all the features of the original dataset, plus four additional columns, one for each of these four classifiers, describing the probability with which the classifier correctly predicts the class label of that record. This process is seen in Fig. 3.10.

Record #s	f_1	f_2	...	$f_{\|F\|}$	sc_1	sc_2	sc_3	sc_4
1,2	1	0	1	1	1	2	1	0
3,4	0	1	0	0	0	1	2	1
5	1	0	1	0	0	0	1	1

(a) Grouped Dataset with Spanning Classifiers

Record #	f_1	f_2	...	$f_{\|F\|}$	c_1	c_2	sc_3	sc_4
1	1	0	1	1	1	1	0	0
2	1	0	1	1	0	1	1	0
3	0	1	0	0	0	0	1	0
4	0	1	0	0	0	1	1	1
5	1	0	1	0	0	0	1	1

(b) Per-Record k-hot Performance of Spanning Classifiers

Record #s	f_1	f_2	...	$f_{\|F\|}$	sc_1	sc_2	sc_3	sc_4
1,2	1	0	1	1	0.5	1.0	0.5	0
3,4	0	1	0	0	0	0.5	1	0.5
5	1	0	1	0	0	0	1	1

(c) Algorithm Selection Dataset

Figure 3.10.: Computing the Algorithm Selection Dataset from the Grouped Dataset

3.5.2. Methodology

The algorithm selection dataset allows for the dynamic selection of algorithms (from a collection of the trained, spanning classifiers identified in Sec. 3.3) at the time of deployment. Since it is the case that for each record in the training data, there is at least one classifier in the spanning set of classifiers that has the best likelihood of correctly classifying the record; a learning algorithm could be trained to correctly predict classifier choice within the spanning set for a given record. Given the superior performance of Random Forests in the previous experiments, a random forest regressor was trained to predict the probability with which each classifier will correctly classify a given record. In keeping with the framework in [1], the implementations of Random Forest regressors in Python's Scikit Learn library [68] were used. While the original experiments in [1] were run using Python's Scikit Learn library [68], in parallel on the nodes of SciNet's Niagara supercomputing cluster, each of which has 40 cores with 202 GB RAM; these regression algorithms were run in parallel on SOSCIP's Compute-x24 nodes, each of which has 24 cores with 96 GB RAM.

However, due to the size of the dataset and the hardware constraints that are imposed on the learning algorithms, a single, multioutput Random Forest Regressor could not be trained. Instead, four single-output Random Forest Regressors were trained to each predict the classification performance of one of the four spanning classifiers. These took as inputs, the metafeatures in each record of the metadataset; and each of these four regressors predicts the performance of the corresponding classifier. The overall classification outcome of the entire system is computed as a function of the outputs from these four regressors and the underlying spanning classifiers (four such functions were tested, and their methodologies and performance are discussed in this section). Each regressor was trained using the same 10x10 fold cross validation methodology in [1] for various numbers of trees in the random forest in $10, 15, 20, ..., 65$, again, in accordance with the range of values of this parameter tested in [1].

3.5.2.1. MostLikely

Given the outputs of the four regressors, the classifier with the highest probability of success (correct classification) is selected to classify the given (previously unseen) record. In order to accomplish this, the data from the unseen record is first featurized (as in [1]) and is then ingested into each of the four regressors. Each regressor then returns the expected classification accuracy of the corresponding classifier. An arbitrary regressor with a highest predicted classification performance is then selected, and the corresponding classifier is tasked with the actual classification task.

The result of this classifier is then returned as the result of the overall system. This is therefore a Frequentist, *a priori* approach to classifier selection. This process is illustrated in Fig. 3.11.

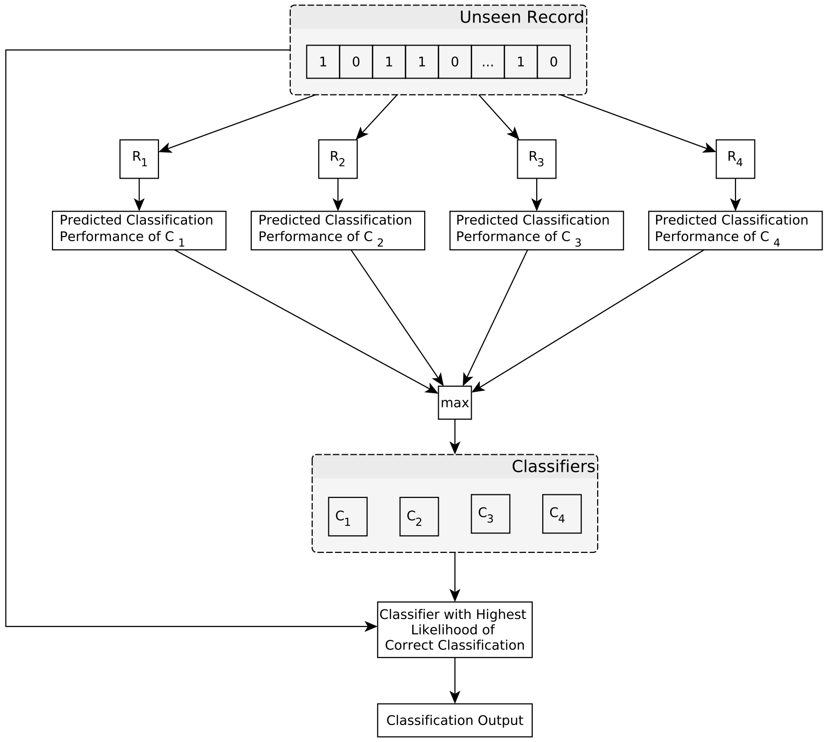


Figure 3.11.: Most Likely Classifier Choice

3.5.2.2. HardVoting

Ignoring the outputs of the four regressors, each spanning classifier votes on the classification outcome. In order to accomplish this, the data from the unseen record is first featurized (as in [1]) and is then ingested into each of the four spanning classifiers (ignoring the regressors, entirely). These classifiers output a classification each, and the most frequent output is returned as the result of the overall system. This is illustrated in Fig. 3.12.

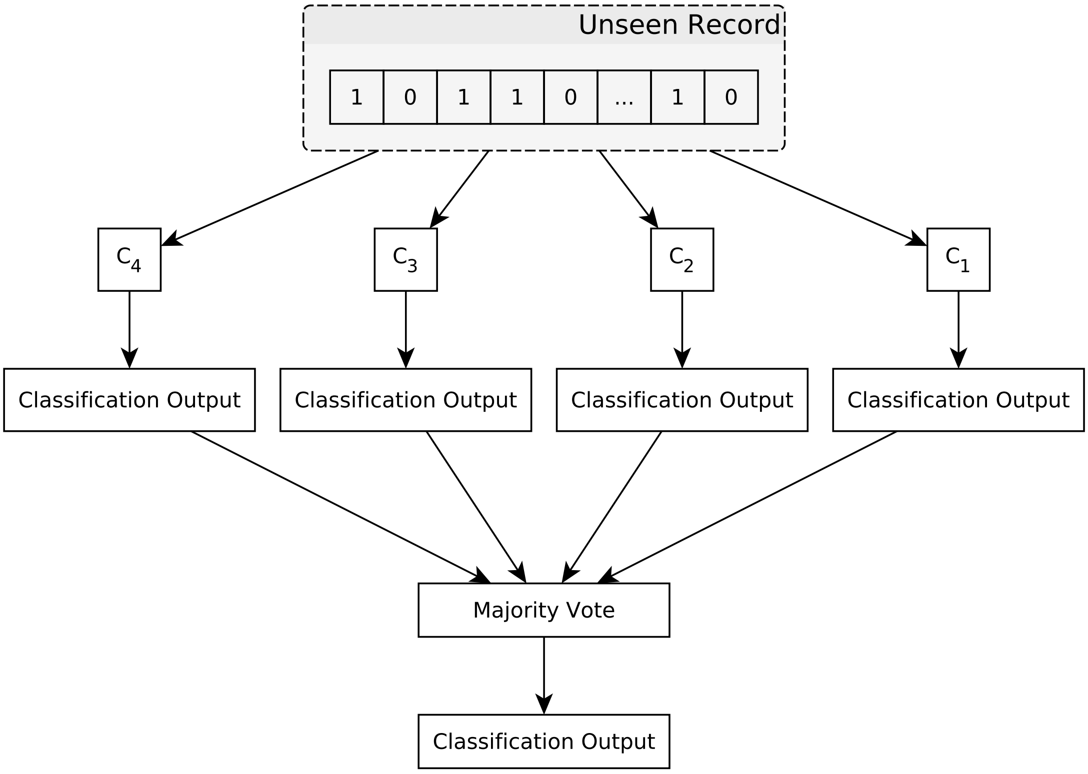


Figure 3.12.: Hard Voting Classifier Choice

3.5.2.3. SoftVoting

Given the outputs of the four regressors, each classifier's vote is weighted by the output of the corresponding regressor. In order to accomplish this, the data from the unseen record is first featurized (as in [1]) and is then ingested into each of the four regressors and their corresponding spanning classifiers. Each classifier outputs a binary class label, which is subsequently multiplied by the probability of that classifier being correct (as predicted by the corresponding regressor). These weighted votes are then averaged and rounded, before being returned as the result of the overall system. This is therefore a Bayesian, *a posteriori* approach to classifier selection. This is illustrated in Fig. 3.13.

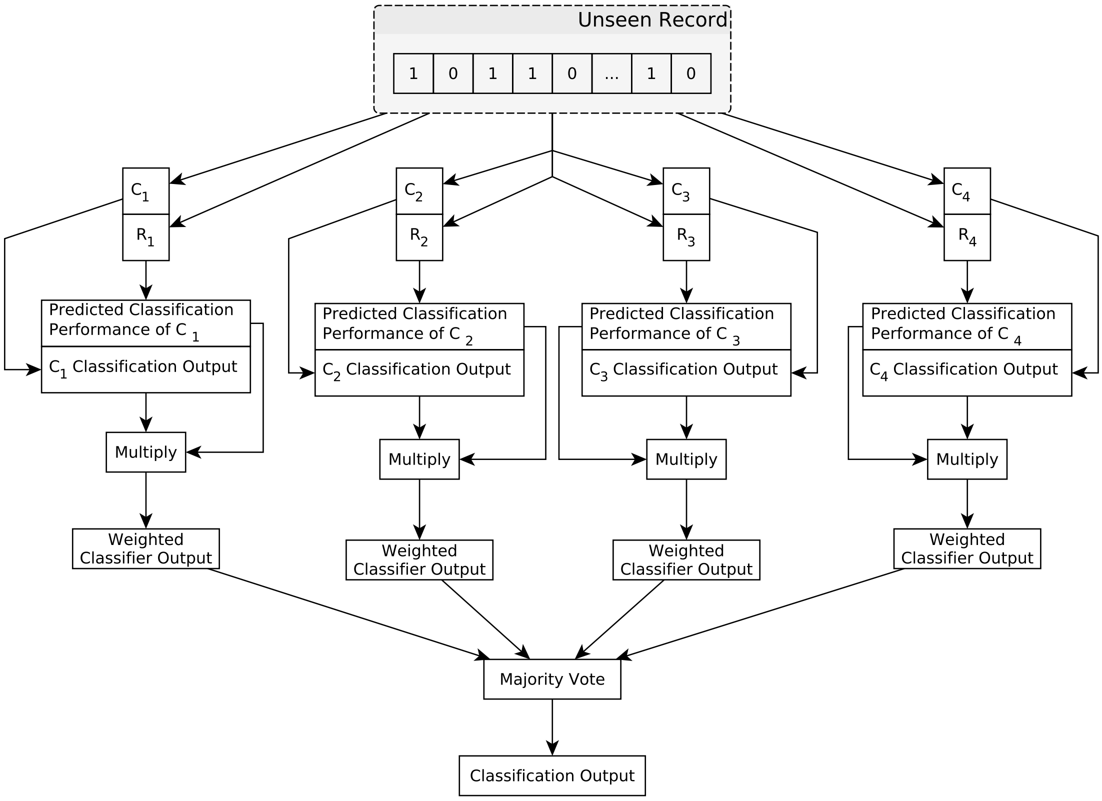


Figure 3.13.: Soft Voting Classifier Choice

3.5.2.4. WeightedSoftVoting

Given the outputs of the four regressors, each classifier's vote is weighted by the output of the corresponding regressor as well as its *a priori* classification performance. In order to accomplish this, the data from the unseen record is first featurized (as in [1]) and is then ingested into each of the four regressors (to compute the classifier's posterior probability of correct classification) and their corresponding spanning classifiers. As well, the number of times each classifier had respectively the best classification performance on the training data was computed as its *a priori* probability of correct classification. Next, each classifier's classification output was multiplied by both its prior and posterior probabilities of correct classification and was returned as its classification outcome. These were then averaged and rounded before returning as the final prediction output of the system. This is illustrated in Fig. 3.14.

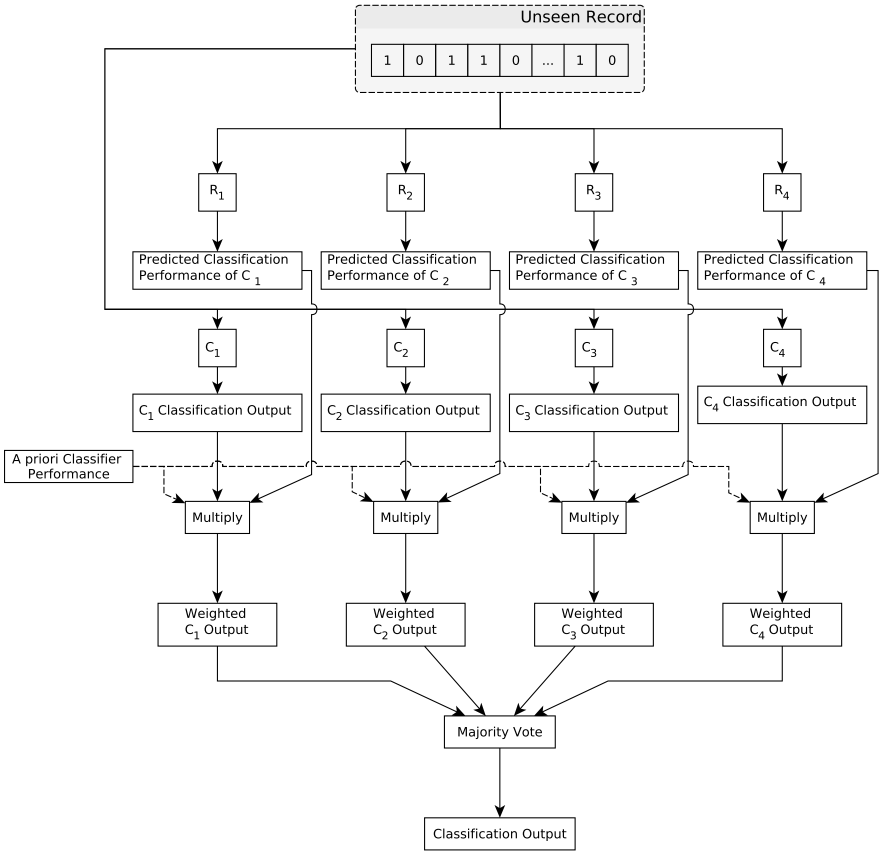


Figure 3.14.: Weighted Soft Voting Classifier Choice

3.6. Adaptive Resource Deployment with Level-4 Soft-Hard Information Fusion

It is intuitive that as the inter-vessel proximity worsens, the backlog of vessels to be served would increase. As a result of this, the deployment of equipment and personnel is needed to also increase throughput and throttle the backlog formation. Describing the optimization as such makes it well suited to be solved by a fuzzy system, as fuzzy systems have been shown to well optimize resource allocation [92, 93, 94]. However, it is unclear as to what the membership functions of such a fuzzy system should be, in order to function optimally. Therefore, these membership functions will be evolved by a multi-objective evolutionary algorithm (MOEA) as described in this section.

3.6.1. Fuzzy System

A Mamdani fuzzy system is used to solve the adaptive resource utilization problem, and its application is discussed in this section.

3.6.1.1. Fuzzifier

This fuzzy system accepts as input, the crisp value of the projected vessel service delay metric (as well as the difference from the delay metric at the previous, most recent poll[4]). The fuzzifier accepts this crisp input and outputs the fuzzy membership values for "low", "medium", and "high" delay. These membership values are computed through the membership functions evolved by the MOEA, which are trapezoidal membership functions (an example is illustrated in Fig. 3.15). Note that in the limiting case, a trapezoidal membership function can converge into a triangular membership function, as shown in Fig. 3.15.

3.6.1.2. Inference Engine

The fuzzy system has the following fuzzy rulebase:

1. If `delay` is low and `delta_delay` is low, decrease deployment

[4] As explained in Sec. 3.6.2, this resource deployment is performed every shift. As a result, the delay metric as the previous, most recent poll is the delay metric computed at the end of the previous shift. The second crisp input is therefore the `delta_delay`, the difference in the delay between the previous and the current shift.

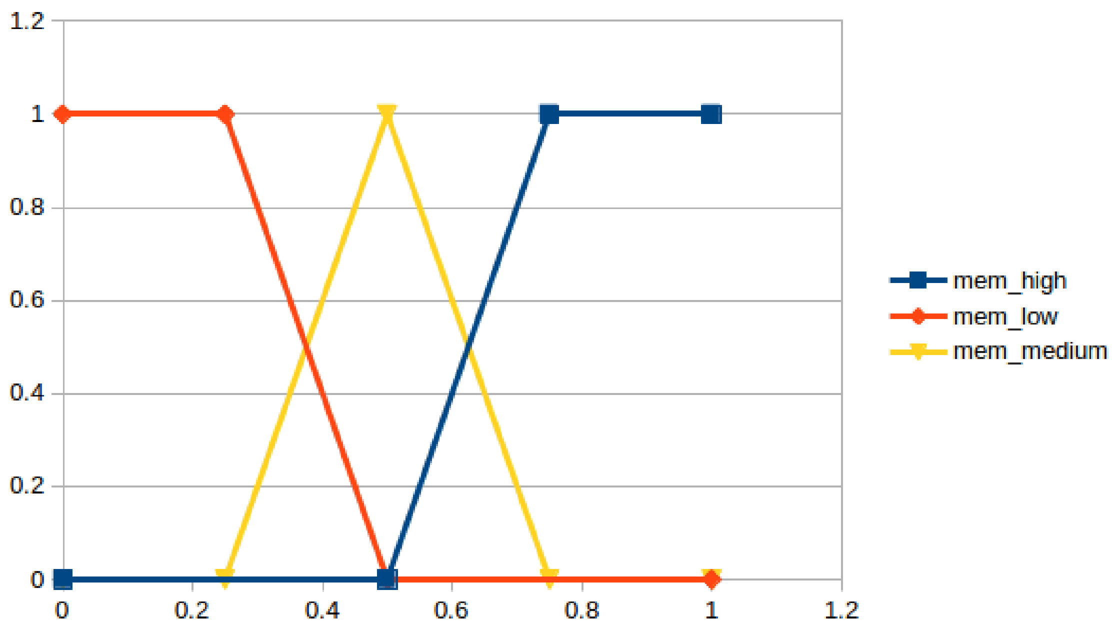


Figure 3.15.: Trapezoidal Membership Function

2. If `delay` is medium and `delta_delay` is low, decrease deployment
3. If `delay` is high and `delta_delay` is low, maintain deployment
4. If `delay` is low and `delta_delay` is unchanging, decrease deployment
5. If `delay` is medium and `delta_delay` is unchanging, maintain deployment
6. If `delay` is high and `delta_delay` is unchanging, increase deployment
7. If `delay` is low and `delta_delay` is high, increase deployment
8. If `delay` is medium and `delta_delay` is high, increase deployment
9. If `delay` is high and `delta_delay` is high, increase deployment

3.6.1.3. Defuzzifier

Given the fuzzy membership functions and the inference engine, the fuzzy system uses a center-of-gravity calculation to determine the change in equipment and personnel deployment at a given time, to respond to the foreseen change in vessel service backlog

3.6.2. Multi-objective Evolutionary Algorithm

In order to optimize the fuzzy system, a MOEA is used to evolve the fuzzy membership functions. This choice of an evolutionary algorithm to optimize the parameters of a fuzzy system come from previous studies [95] that have used evolutionary algorithms to optimize fuzzy systems. The structure and functioning of this MOEA is described in this section.

3.6.2.1. Individual Structure

Each individual is comprised of three chromosomes which encode the values of the vertices of a trapezoidal fuzzy membership, respectively to `low delay`, `medium delay`, and `high delay`. An example of this tri-chromosomal structure is shown in Fig. 3.16.

	A	**B**	**C**	**D**
$\mu_{\texttt{low\_delay}}$	0.33	0.5	0.66	1
$\mu_{\texttt{medium\_delay}}$	0.33	0.5	0.66	1
$\mu_{\texttt{high\_delay}}$	0.33	0.5	0.66	1

Figure 3.16.: Chromosomal Structure for Trapezoidal Individual

$$\text{mem\_low}(x) = \begin{cases} 1 & x < 0.33 \\ \frac{100-100x}{17} & 0.33 \leq x < 0.5 \\ 0 & 0.5 \leq x \end{cases} \tag{3.16}$$

$$\text{mem\_med}(x) = \begin{cases} 0 & x < 0.33 \\ \frac{6}{|x-\frac{1}{2}|} & 0.33 \leq x < 0.66 \\ 0 & 0.66 \leq x \end{cases} \tag{3.17}$$

$$\text{mem\_high}(x) = \begin{cases} 1 & x < 0.5 \\ \frac{100x-100}{17} & 0.5 \leq x < 0.66 \\ 0 & 0.66 \leq x \end{cases} \tag{3.18}$$

3.6.2.2. Fitness

Given an individual of the MOEA which encodes a set of fuzzy membership functions, the projected delays are computed as follows. First, the known vessel arrival times (based on ground truth, previously mined from AIS data) are simulated. Incoming vessels are then serviced with the currently deployed resources. Additionally, hard data in the form of the incoming vessel schedule is ingested and the impending shipping container processing load is computed. At the end of the current day (three eight-hour shifts), the backlog of containers to be processed is computed and compared with the backlog from the end of the previous day. The daily situation report is then synthesized using this information (as previously described in Sec. 3.2.14).

This situation report (soft data) is then ingested to compute the projected delay on a $[0, 1]$ scale as follows. A keyword search is performed on the situation report, over a lexicon including the synonyms of the words "`congestion`" and "`delay`". If `"delay"` is found in the situation report, then `"congestion"` is not searched for, since mentions of delays describe impending vessel service delays more accurately than mentions of congestion which are simply a reason thereof. If no keyword from the lexicon is found in the situation report, a projected delay of 0 is reported. If a keyword is found, however, a projected delay of 0.5 is noted, pending further analysis. Once the keyword is found, any adjectives modifying the keyword are searched for by simply searching the words appearing prior to the found keywords. If not adjectives are found, then the previously noted delay of 0.5 is reported. However, if an adjective is found, then it is tested for membership within two disjoint lexicons, namely "diminutive" and "exaggerative", mined from real-world situation reports. The "diminutive" lexicon includes adjectives that decrease the intensity of the word they modify such as "`small`", "`minor`", "`some`", etc. On the other hand, the "exaggerative" lexicon includes adjectives that increase the intensity of the word they modify such as "`significant`", "`large`", etc. Given these lexicons, if the found adjective is a member of the "diminutive" lexicon, then the reported delay value must be reduced from the previously noted value of 0.5. In order to achieve this effect, it is multiplied by a uniformly distributed random number in $[0.7, 1]$. Conversely, if the found adjective is a member of the "exaggerative" lexicon, then the reported delay value must be increased from the previously noted value of 0.5. In order to achieve this effect, it is multiplied by a uniformly distributed random number, drawn from $[1, 1.3]$. Finally, the modified delay value is reported as the projected delay on a $[0, 1]$ scale, which is then used as the crisp input to the fuzzy system described by the given individual.

The fuzzy system then returns the resource deployment which is then used to compute the number of shipping containers processed in the following shifts. Since each crane (and operator) can process one container every two minutes, the container processing capacity of the deployment of resources over a shift is the number of two-minute segments in the shift scaled by the resource deployment. The fitness of the given individual is then reported as a point on a two dimensional non-dominated front spanning the sum of the service times for all vessels, and the total resource deployment (summed over all shifts).

3.6.2.3. Selection

Since crossover requires two individuals, a selection mechanism is required to select these two individuals from the population. First, the fitness of each individual is computed as previously described, and the individuals are sorted into fitness fronts. Next, two parents are independently, randomly selected such that a random individual from front i is selected with probability $\frac{1}{i+1}$ (the $i+1$ in the denominator allows for the selection of an individual in the Pareto front to be selected with probability 0.5 instead of 1) [67].

3.6.2.4. Crossover

Crossover is performed by means of a fitness proportional variant of the Weighted Arithmetic Crossover [96], which we will call "FitWAM". However, since a fitness proportional crossover requires a scalar (i.e. uni-dimensional) fitness measure, a relative fitness measure (F_r) is defined. This is computed as the average distance from the mean of a given individual, along each dimension of the two-dimensional fitness plane, from the population's average along each dimension. This is more formally defined in Eq. 3.19 and Eq. 3.20.

$$\overline{F_i} = \frac{\sum_{x=1}^{|P|} F_i P_x}{|P|} \tag{3.19}$$

$$F_r(P_x) = \frac{1}{2} \cdot \left[\sum_{i=1}^{2} F_i(P_x) - \overline{F_i} \right] \tag{3.20}$$

where

F_r is the relative fitness measure

$F_i(P_x)$ is the fitness of individual P_x along objective i

P is the population of all individuals

This gives us a relative scalar measure with which to compare individuals P_1 and P_2. Next, the child individual is computed by assigning the value of each gene to be the weighted average of the corresponding genes of each parent, weighted by the relative fitness measure. An example of this is seen in Fig. 3.17.

	A	**B**	**C**	**D**
membership to `low_congestion`	0.33	0.5	0.66	1
membership to `medium_congestion`	0.33	0.5	0.66	1
membership to `high_congestion`	0.33	0.5	0.66	1

(a) Parent Individual P_1 ($F_r = 1$)

	A	**B**	**C**	**D**
membership to `low_congestion`	0	0.5	0.66	1
membership to `medium_congestion`	0	0.5	0.66	1
membership to `high_congestion`	0	0.5	0.66	1

(b) Parent Individual $P_2(F_r = 3)$

	A	**B**	**C**	**D**
membership to `low_congestion`	0.0825	0.5	0.66	1
membership to `medium_congestion`	0.0825	0.5	0.66	1
membership to `high_congestion`	0.0825	0.5	0.66	1

(c) Child Individual

Figure 3.17.: Example Crossover

3.6.2.5. Mutation

Mutation is defined as changing the value of one gene in one chromosome to another random, feasible value. For example, mutating the value for B in a trapezoidal individual results in a different value of B, while still being constrained to $A \leq B \leq C$, as shown in Fig. 3.18.

	A	**B**	**C**	**D**
membership to `low_congestion`	0.33	0.5	0.66	1
membership to `medium_congestion`	0.33	**0.5**	0.66	1
membership to `high_congestion`	0.33	0.5	0.66	1

(a) Original Individual

	A	**B**	**C**	**D**
membership to `low_congestion`	0.33	0.5	0.66	1
membership to `medium_congestion`	0.33	**0.45**	0.66	1
membership to `high_congestion`	0.33	0.5	0.66	1

(b) Mutant (mutated `B` value in `membership_to_med_congestion`

Figure 3.18.: Example Mutation (notice the changed `B` value in membership to `medium_congestion`)

3.6.2.6. Termination

Since the optimum value is unknown, it is impossible to know whether a new Pareto front will be generated. Therefore, the MBGM stopping methodology [97] is used here. Specifically, the frequency at which new Pareto fronts are generated is tracked. This is described by the number of generations between the creation of each subsequent new Pareto front, the largest of which is the maximum number of generations between any two successive new Pareto front creations. If at any given time, more than twice as many generations have passed without the creation of a new Pareto front, it is unlikely that any new Pareto front will be generated. Thus, the MOEA is stopped, and the current Pareto front is returned as the result of evolution. However, since the search space is substantially large, fitness improvements were not immediately observed, this termination criterion was applied only after 100 generations.

Experiment Environment

The computational experiments were run independently on a consumer laptop with an Intel(R) Core(TM) i7-3520M CPU @ 2.90GHz CPU and 16GB RAM.

3.7. Summary

Drawing from several studies across multiple disciplines, multiple factors have been considered for the stated purposes of predicting shipping container damage and the causes thereof. Conventional wisdom from industry has also been captured in a survey against which the results of our study have been compared. The published results contradict expert opinions from the industry and warrant further study. Further, classifier accuracy has been improved with the inclusion of Leave One Batch Out learning.

4. Results

4.1. Classifier Claims Prediction

Data was synthesized based on survey responses (as discussed in Sec. 3.2), and a study was conducted to determine the factors most correlated with shipping container damage on maritime vessels. Over 70 computational learning algorithms from Python's `scikit-learn` library were used to learn the correlations between the features in the data and container damage claims. These included some rudimentary neural networks, but no deep learning strategies. This is because this thesis is the first study to explore this problem and simpler models with fewer tunable parameters were chosen over models with more tunable parameters and larger training times, such as deep neural networks, convolutional neural networks, etc.

The performance of the eleven best classifiers are shown in Tab. A.1, while the relative importances of the various features in the dataset are shown in Fig. 4.1. These discovered relative feature importances are counter to the expert opinions captured in the surveys.

This study revealed that opinions held by experts in the industry did not align with the discovered causes of shipping container damage from the data. Since investigations are triggered by incoming claims, false negatives are less favorable than false positives. It is therefore important to compare the accuracy of classifiers that

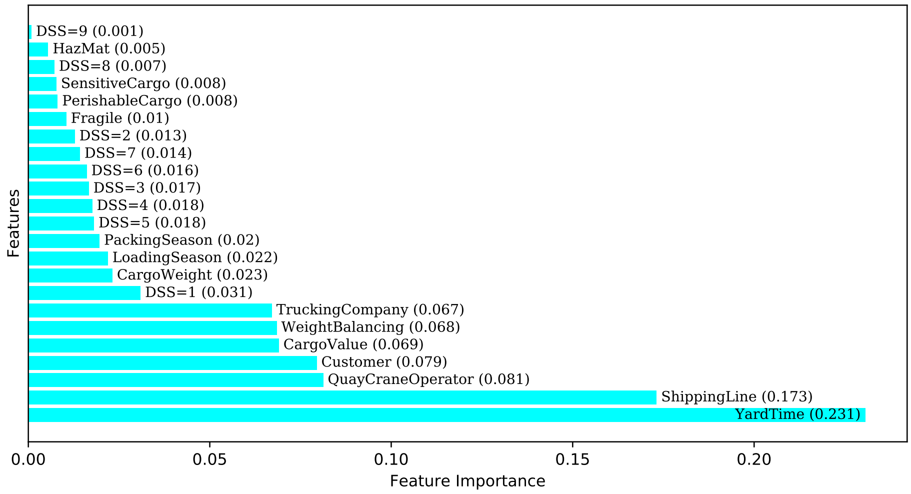


Figure 4.1.: Relative Feature Importances

have equivalent AUC (seen in Tab. A.1). The superior performance of Random Forests suggests that nonlinear and ensemble methods may be applicable. Analysis of trained decision trees and Random Forests reveals relative feature importances (see Fig. 4.1). From this, it is clear that the amount of time spent by a container in the storage yard is the most revealing feature in predicting container damage claims. While a container's cargo value was expected to be an important feature, the quay crane operator, shipping line, and time spent in the storage yard yield the highest container claims predictability, contrary to expert opinion[1].

Analyzing the most important features reveals the true correlations between the data features and shipping container damage, seen in Tab. 4.1. This shows that cargo value, hazardousness, longevity, sensitivity, mass distribution, storage time, and exposure to rough seas correlate strongly positively with filed claims.

On the other hand, calm sea states have strong negative correlation, as expected. Additionally, the packing and loading seasons of shipping containers correlate weakly

[1]The survey results showed that cargo value, hazardous and/or sensitive cargo were the most important attributes in predicting insurance claims

Feature	**Correlation**
Cargo value	Strongly positive correlation
Presence of hazardous cargo in the container	
Cargo longevity	
Cargo sensitivity	
Mass distribution of cargo in the shipping container	
Amount of time spent in the storage yard	
Exposure to rough seas along voyage from source to destination ports	
Exposure to calm seas along voyage from source to destination ports	Strongly negative correlation
Container packing season	Weak negative correlation
Container loading season	
Cargo fragility	Very weak positive correlation
Quay crane operator	Strong positive correlation

Table 4.1.: Discovered Feature Correlations

with container claims (25% support and 13% confidence in the relevant association rules). Logistics companies are also found to be weak indicators of shipping container damage (18% support, 11% confidence).

Cargo Fragility is found to very weakly correlate with container damage claims (Pearson R coefficient of 3.7×10^{-4} and 50% support, 50% confidence for relevant association rules), again counter to expert opinion. This could be due to proper container packing compensates for cargo fragility, while quay crane operator error dominates in human error (with 8% support and 4% confidence).

4.2. Improving Container Damage Claims Classifier Performance Veracity with Leave One Batch Out Training

From the results presented in Appendix A of the methodologies discussed in Sec. 3.4.1, Sec. 3.4.2, and Sec. 3.4.3, it is evident that performing the classification without the weather features yields better classifier performance than when the weather features are included during classification. This is counter to the expectations outlined at the outset. This could potentially be explained by the dataset synthesis methodology (see Sec. 3.2); specifically, the non-weather features are drawn from simple distributions that are easily learned by machine learning algorithms. Therefore, these results do not adequately address the concern of learning bias requiring further analysis.

Following up the inconclusive analysis in Sec. 3.4.1, the dataset is partitioned based on the values of the weather features (as described in Sec. 3.4.2). One such partition is held out as a validation set, while training and testing are performed on the remainder of the dataset. The results from these experiments (shown in Tab. A.3 and) show that the classifiers outperform their counterparts in Sec. 3.4.1. This suggests that this cross-validated training method is superior to training method and warrants more investigation for a new publication as it promises better generalization.

Given the performance increase noted in Fig. 4.2, the extension of that methodology (used in Sec. 3.4.3) promises better results. However, since this observed to not be the case (see Tab. A.4), concluding that the former training methodology affords better generalizability than the latter. This is especially relevant to information fusion effectiveness as these experiments have been performed with data restricted to a three month POI (and therefore, limited variance in weather patterns across the dataset). Performing these experiments against a larger data set with a one-year POI will reconfirm the conclusions about the generalizability of LOBO methodology.

Yet, the argument still holds that the superior performance of using a validation batch over performing cross-validation with LOBO could be an artifact of the restricted POI of the dataset which captures only a subset of annual weather patterns. Unfortunately, since no other maritime voyage track data is available, this criticism cannot be further investigated at the moment. However, negotiations are currently under way to acquire such data from data vendors to make this investigation possible.

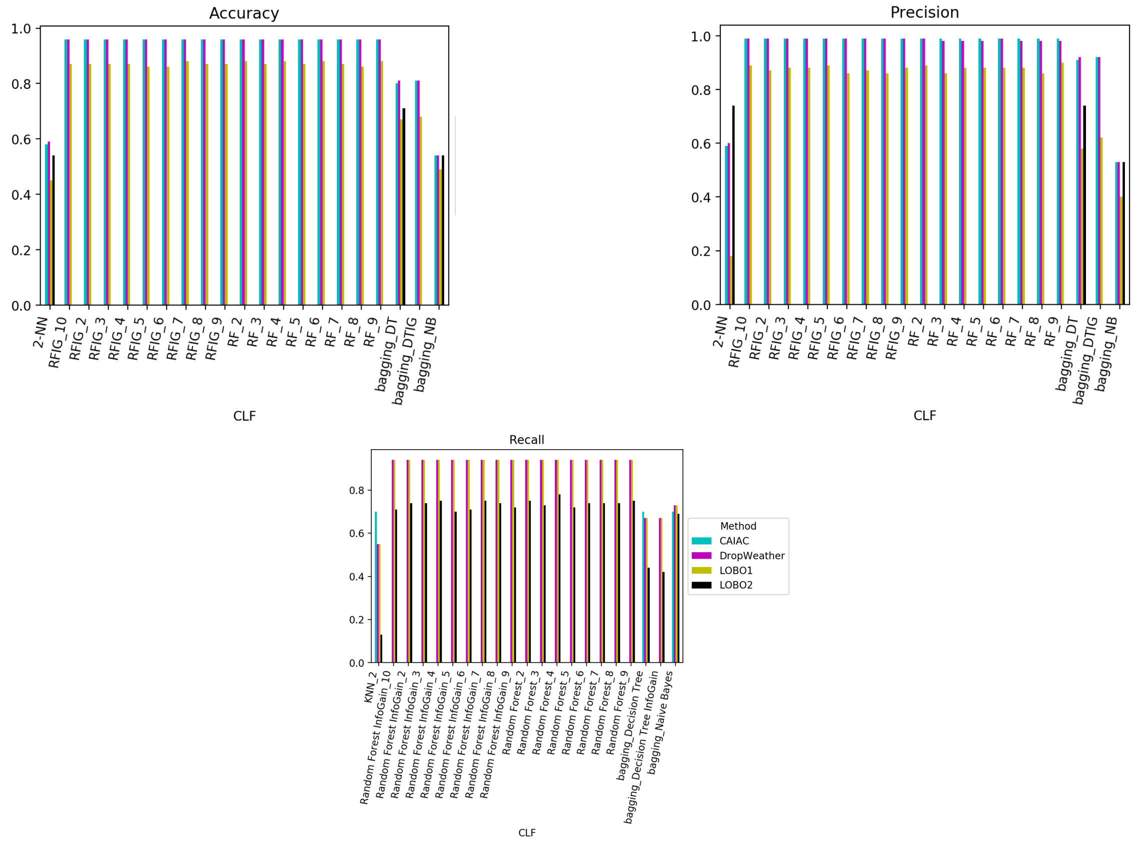


Figure 4.2.: Predictive Performance without Weather Data and Using LOBO Methodologies

4.3. Metadata Based Algorithm Selection

Given the relative performances of the various classifiers in identifying shipping container damage (see Sec. 3.3), classifier performance may be improved upon by selecting the appropriate classifier to use at a given time [98]. This is achieved by training classifiers on a dataset comprised of the data used in [1], in which each record is augmented with the performance of each of the classifiers used (a working example of this is shown in Fig. 3.8 with more detailed technical explanation in Sec. 3.5). Once correlations between data artifacts and classifier performance have been learned, they can be used to predict the classifier with the best performance for new, unseen data. Thus, a pool of classifiers is dynamically chosen from, in order to further improve overall classification performance. The performance of each of the four methodologies used to accomplish this are seen in Fig. 4.3.

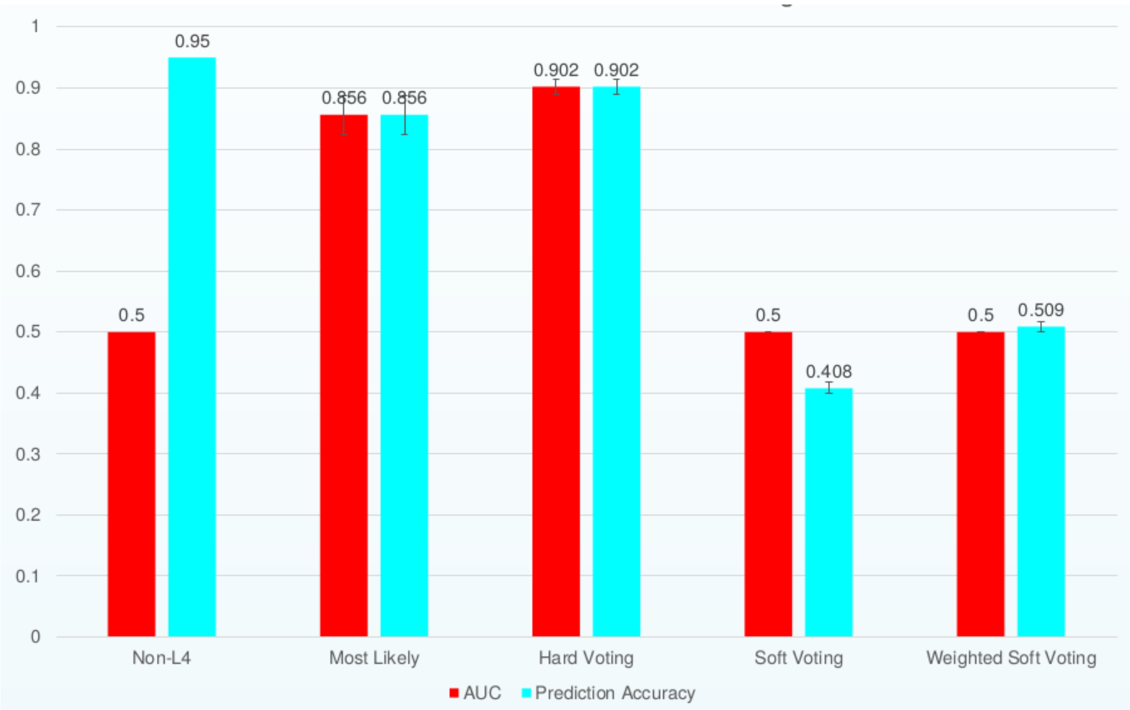


Figure 4.3.: Metalearning Methodology Performance

4.3.1. Example

It is well known that certain CI algorithms perform better under certain operational conditions (such as noisy data, incomplete data, etc) than do others. Therefore, performance may be improved by performing a meta-analysis to discover correlations between data artifacts and classifier performance. This affords the ability to select the best classifier to use on a new, unseen record, to yield the best classification performance.

So for example, if it is discovered that a Decision Tree has the best performance when a shipping container has perfectly balanced cargo weight (but performs poorly otherwise), then this is the classifier that will be used when a new, unseen record is observed to have perfectly balanced cargo weight.

4.4. Adaptive Resource Deployment with Level-4 Soft-Hard Information Fusion

In order to compare the performance of a MOEA-optimized fuzzy system to control resource deployment, they must be compared with the assessment of current industry practice. As mentioned in Sec. 3.5.1, the real-world resource deployment (ground truth) is mined from the available AIS data. These are compared with the performance of the optimized system in Tab. 4.2.

The MOEA described in Sec. 3.6.2 is run 30 independent times (for statistical validity) and the Pareto fronts of each of those runs (along with the best performant fuzzy system over the entire evolutionary process) is reported. The mean performance (along with their 95% confidence intervals) of the individuals from these 30 Pareto fronts (as well as the 30 best performant individuals) is shown in Tab.

Tab. 4.2. Further, the mean characteristics of the trapezoidal membership functions along with their 95% confidence intervals are shown in Tab. 4.3 and illustrated in Fig. 4.4.

	Mined, Real-World Performance	Optimized Performance
Number of Crews Used	63	23.654 ± 0.05
Total Service Time	77 days, 12 hours, 51 min, and 55 sec.	4 days, 4 hours, 27 min, 53 sec

Table 4.2.: Performance of Evolved Fuzzy Systems

`delay`	$\mu_{\texttt{low}}$	$\mu_{\texttt{medium}}$	$\mu_{\texttt{high}}$
A	0	0	0.377 ± 0.008
B	0	0.289 ± 0.008	0.682 ± 0.009
C	0.366 ± 0.009	0.529 ± 0.01	1
D	0.690 ± 0.008	0.771 ± 0.007	1

Δ`delay`	$\mu_{\texttt{low}}$	$\mu_{\texttt{medium}}$	$\mu_{\texttt{high}}$
A	-1	-1	-0.170 ± 0.019
B	-1	-0.311 ± 0.017	0.446 ± 0.017
C	-0.188 ± 0.018	0.135 ± 0.017	1
D	0.373 ± 0.016	0.570 ± 0.015	1

Table 4.3.: Mean Characteristics of Evolved Fuzzy Systems

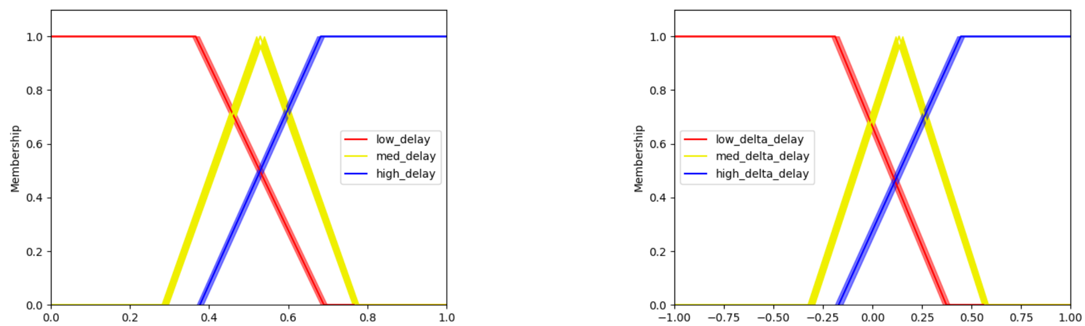


Figure 4.4.: Mean Fuzzy Membership Functions

The resource deployment mined from real-world AIS data shows that a total of 63 crews were used for overall vessel service. Each crew is comprised of one quay crane operator and all supporting personnel and equipment. Each quay crane requires 3-5 internal shunt trucks (to transport the shipping container within the port), each of which requires one operator. Each shunt truck, in turn, requires one forklift operator (to load a container between a storage pile and shunt truck) [46]. Therefore, each quay crane operator requires an additional 6-10 personnel. Therefore a single crew comprises of 7-11 personnel, deployed for an integer number of shifts.

The MOEA-optimized fuzzy system shows that 23-24 crews are required to perform the same vessel service, accounting for a 62.45% $\pm$ 0.0008% increase in per-crew productivity. Thus, this MOEA-optimized fuzzy system for crew deployment would save a port 62% in just personnel wages.

Such improvements in resource deployment classically come at the cost of worsened execution time (in this case, vessel service time). However, this does not appear to be the case in this study. A reduction of the overall service time from 1860 hours to 100 hours shows that not only does this system perform the same work with fewer resources, but it does so with approximately 94.6% improvement in service time (the service schedule mined from real-world data and the service schedule induced by the optimized fuzzy system are shown in Fig. 4.5). This is most likely due to the fact that the optimized fuzzy system deployed multiple crews for certain shifts whereas the mined real-world data shows a maximum of only one crew on any given shift.

In order to establish the generalizability of this methodology, the optimization was repeated with data pertaining to the Port of Halifax and Victoria Port (in Honk Kong). Similar fuzzy systems were evolved for each port, yielding similar optimization results.

The results of the optimization on the Port of Halifax are shown in Tab. 4.4, Tab. 4.5, and Fig. 4.6; while the results for Victoria Port (on both the real-world and the

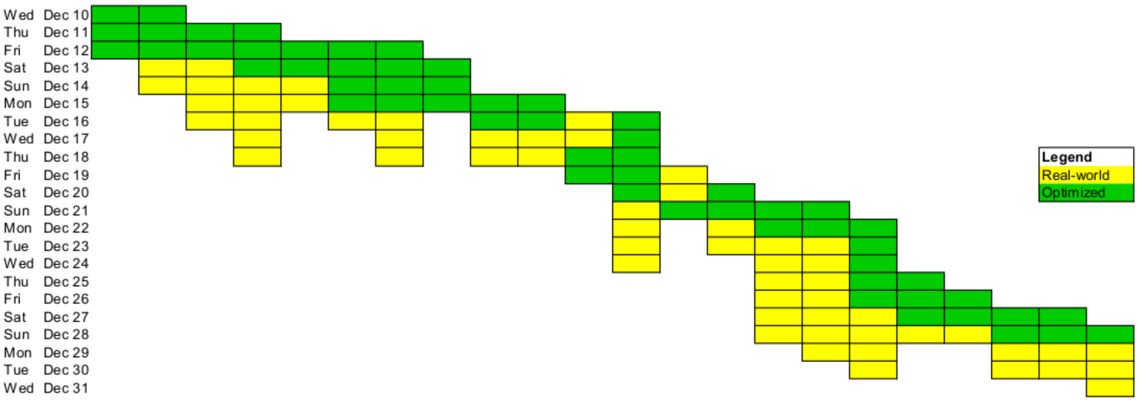


Figure 4.5.: Vessel Service Schedules

doubled datasets) are shown in Tab. 4.6, Tab. 4.7, and Fig. 4.8. Finally, a sample of the resultant resource deployment schedule for the Port of Halifax are shown in Fig. 4.7 and for Victoria Port in Fig. 4.9.

	Mined, Real-World Performance	Optimized Performance
Number of Crews Used	33	3
Total Service Time	12 days, 11 hours, 50 minutes, 41 seconds	9 hours, 17 minutes, 54 seconds

Table 4.4.: Performance of Evolved Fuzzy Systems at Port of Halifax

delay	$\mu_{\texttt{low}}$	$\mu_{\texttt{medium}}$	$\mu_{\texttt{high}}$
A	0	0	0.4 ± 0.009
B	0	0.32 ± 0.008	0.72 ± 0.007
C	0.29 ± 0.009	0.56 ± 0.009	1
D	0.68 ± 0.009	0.76 ± 0.007	1

Δdelay	$\mu_{\texttt{low}}$	$\mu_{\texttt{medium}}$	$\mu_{\texttt{high}}$
A	-1.0	-1.0	-0.2 ± 0.019
B	-1.0	-0.31 ± 0.018	0.38 ± 0.017
C	-0.33 ± 0.018	0.09 ± 0.017	1.0
D	0.35 ± 0.16	0.54 ± 0.014	1.0

Table 4.5.: Mean Characteristics of Evolved Fuzzy Systems at Port of Halifax

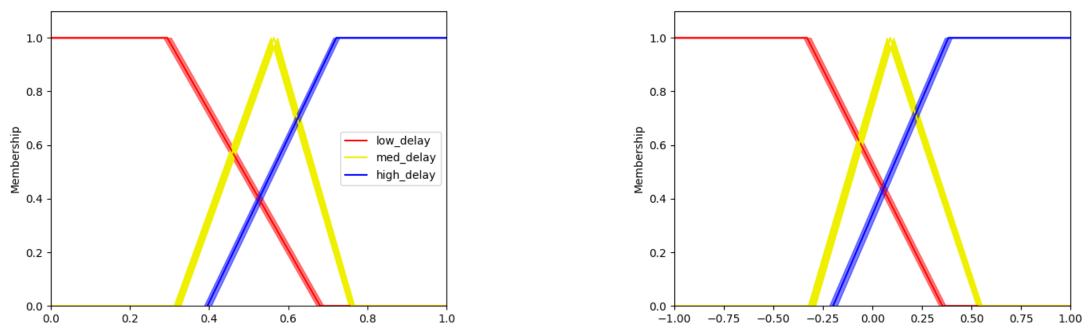


Figure 4.6.: Mean Fuzzy Membership Functions for Fuzzy System for Port of Halifax

	Mined, Real-World Performance	Optimized Performance
Number of Crews Used	88	23.097 ± 0.03
Total Service Time	73 days, 10 hours, 57 hours, 7 seconds	1 day, 15 hours, 18 minutes, 48 seconds

Table 4.6.: Performance of Evolved Fuzzy Systems at Victoria Port

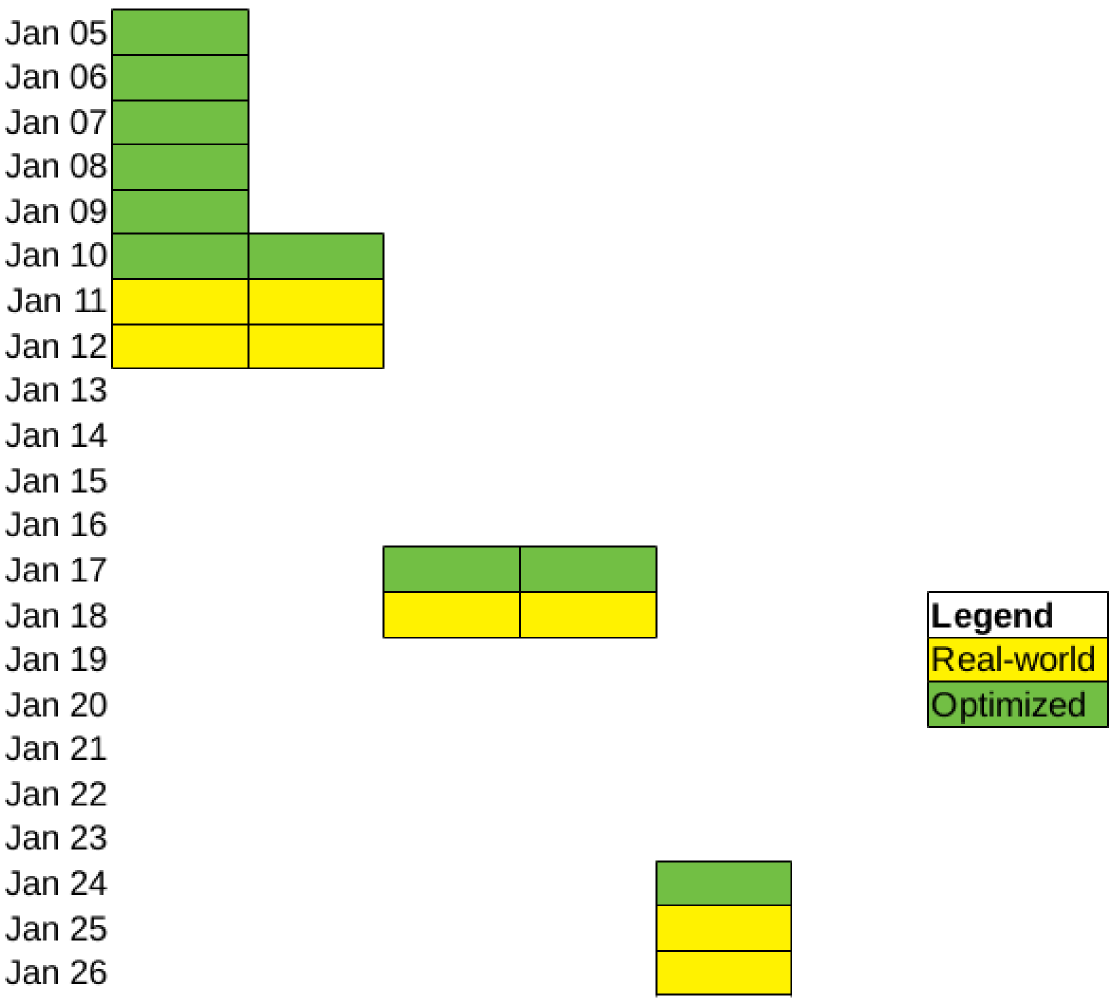


Figure 4.7.: Optimized Service Schedule for Port of Halifax

`delay`	$\mu_{\texttt{low}}$	$\mu_{\texttt{medium}}$	$\mu_{\texttt{high}}$
A	0	0	0.35 ± 0.008
B	0	0.29 ± 0.007	0.67 ± 0.009
C	0.34 ± 0.01	0.53 ± 0.008	1
D	0.670.008	0.75 ± 0.007	1

Δ`delay`	$\mu_{\texttt{low}}$	$\mu_{\texttt{medium}}$	$\mu_{\texttt{high}}$
A	-1.0	-1.0	-0.27 ± 0.017
B	-1.0	-0.39 ± 0.017	0.37 ± 0.016
C	-0.36 ± 0.017	0.09 ± 0.017	1.0
D	0.30 ± 0.018	0.48 ± 0.017	1.0

Table 4.7.: Mean Characteristics of Evolved Fuzzy Systems at Victoria Port

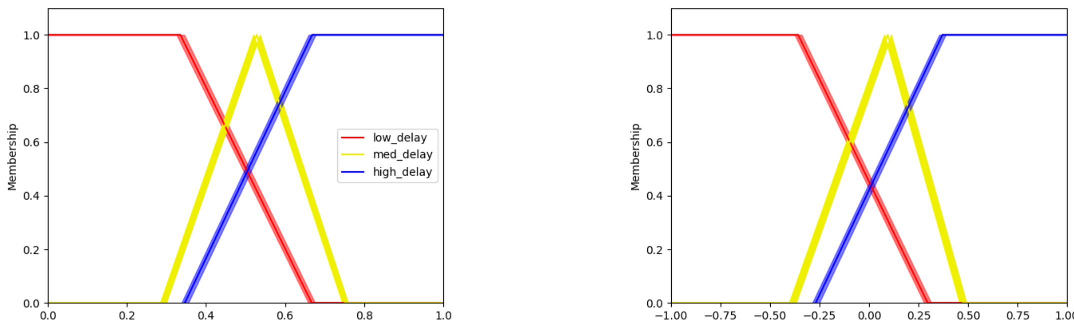


Figure 4.8.: Mean Fuzzy Membership Functions for Fuzzy System for Victoria Port

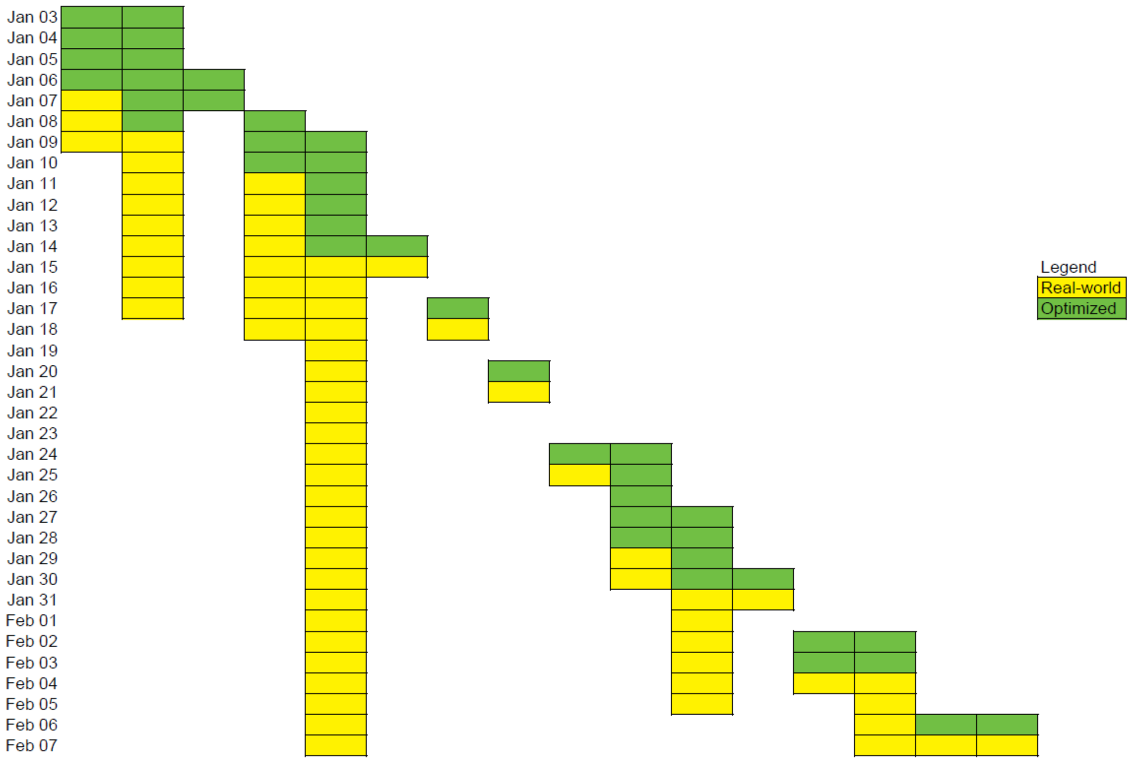


Figure 4.9.: Optimized Service Schedule for Port of Halifax

4.4.1. Data Source Selection

In order to meaningfully select between data sources, each data source was evaluated for its quality. The optimality of a data source is determined by training a model on data exclusively from this source and testing the performance of the trained model. The training and testing were performed in the same methodology as described in Sec. 3.6. In order to create the datasets for each data source, the original dataset was split into six sets, each one corresponding to one of the six AIS data sources present in the original dataset. The number of records from each data source is specified in Tab. 4.8 and shown in Fig. 4.10. Since Source 1 and Source 5 each have approximately 50% of all the records in the entire dataset, they were used for this analysis. On the other hand, since Source 2, 3, 4, and 6 contained a negligible number of AIS records, they did not provide sufficiently many records to perform this analysis and were preemptively filtered out.

Source	Number of Records
Source 1	4,048,309
Source 2	2,243
Source 3	408
Source 4	12,051
Source 5	3,932,275
Source 6	1

Table 4.8.: Distribution of Records by Data Source

With the separated data from Sources 1 and 5, three datasets were created. The first contained data from only Source 1, the second from only Source 5, and the last from both Source 1 and Source 5. Next, three models were evolved using the same methodology as described in Sec. 3.6, one using each of the three new datasets. The resulting models were then run to determine the two-dimensional fitness values of their respective performances, so that they could be compared. The quality of each data source is measured as the optimality of the model resulting

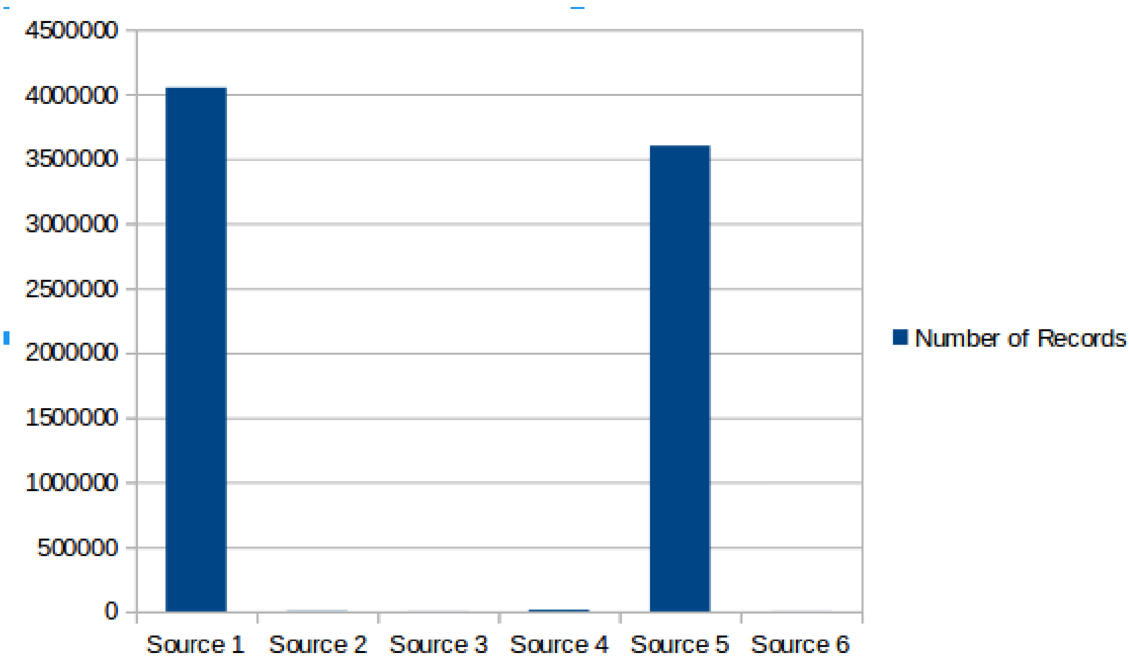


Figure 4.10.: Distribution of Records by Data Source

from training on the corresponding dataset. Since each data source accounts for approximately half the data in the original dataset, the equivalent of a model trained on the original dataset is expected to complete vessel service in approximately half the time with approximately half the resource deployment. This is therefore the benchmark against which models trained on either dataset will be compared. This expectation is shown in Tab. 4.9.

In contrast to the expectations laid out in Tab. 4.9, the results of the optimization performed on these datasets is shown in Tab. 4.10. The results show that Source 1 is of better quality than Source 5 since the fitness of the optimizer trained with data from it dominates the fitness of the optimizer trained on data from Source 5. However, considering that Source 1 describes fewer vessel service instances than Source 5 (see Tab. 4.11), it is possible to attribute this performance improvement to sample bias. Investigating this would require a larger dataset from Source 1 and Source 5, which are left as areas of further study, out of the scope of the current

(a) Port of Montreal

	Optimized Performance (with All Data Sources)	Optimizer Expectation (with Source 1 or 5)
Number of Crews Used	23.654 ± 0.05	11.827 ± 0.03
Total Service Time	4 days, 4 hours, 27 min, 53 sec	2 days, 2 hours, 13 min, 56 sec

(b) Port of Halifax

	Optimized Performance (with All Data Sources)	Optimizer Expectation (with Source 1 or 5)
Number of Crews Used	3	2
Total Service Time	9 hours, 17 minutes, 54 seconds	4 hours, 38 minutes, 57 seconds

(c) Victoria Port

	Optimized Performance (with All Data Sources)	Optimizer Expectation (with Source 1 or 5)
Number of Crews Used	23.097 ± 0.03	11.549 ± 0.02
Total Service Time	1 day, 15 hours, 18 minutes, 48 seconds	19 hours, 39 minutes, 24 seconds

Table 4.9.: Optimizer Performance Expectation

work.

Sample bias in Source 1 aside, the results show an improvement in the trained model when using data from both Source 1 and Source 5. This improvement confirms that excluding Sources 2, 3, 4, 6 from the training data does improve the performance of the optimizer, supporting the arguments for data source selection within the original dataset. This combined optimizer does not dominate over the optimizer trained on Source 5. Yet, it only improves upon the set benchmark (unlike its counterpart), which further supports the inclusion of data from Source 1 when using Source 5.

The results show that the evolved fuzzy system is able to easily handle double the service throughput without any significant additional resource requirements, making this a very robust optimized solution. There is a noted insignificant increase in the resource deployment at Victoria Port. However, since both the real-world load and the synthetically doubled load, both require 24 cranes, this difference is considered negligible. The limits of such an optimized resource deployment model are difficult to identify, without additional data and are therefore left as future directions of investigation.

(a) Optimization Results

Data Source	Number of Crews Used	Total Service Time
Real-world Performance	63	77 days, 12 hours, 51 min, and 55 sec.
Optimization Using all Data Sources	23.654 ± 0.05	4 days, 4 hours, 27 min, 53 sec
Optimization Using Data Source 1	9.26 ± 0.03	1 day, 8 hours, 15 min, 41 sec
Optimization Using Data Source 5	12.27 ± 0.04	1 day, 16 hours, 46 min, 54 sec
Optimization Using Data Sources 1 and 5	22.367 ± 0.05	4 days, 3 hours, 14 min , 56 sec

(b) Comparison to Expectations

Data Source	Improvement on Crew Usage	Improvement on Total Service Time
Optimization Using Data Source 1	21.7%	35.78%
Optimization Using Data Source 5	-3.8%	18.81%
Optimization Using Data Sources 1 and 5	5.4%	1.21%

Table 4.10.: Optimization Results on Split Datasets

Data Source	Number of Usable Vessel Services to Optimize
All Data Sources	27
Data Source 1	15
Data Source 5	22
Data Sources 1 and 5	27

Table 4.11.: Vessel Services Per Data Set

4.4.2. Optimizer Robustness

In an attempt to saturate the resource utilization, a new data set was created for the Port of Halifax and Victoria Port. This data set was synthetically imputed to contain twice as many voyages as the original data set. This was accomplished by creating a duplicate, "twin" voyage for each voyage seen in the original dataset. The identifying information for the vessel and the voyage (namely the voyage ID and the vessel MMSI and IMO) for these twin voyages were randomly reassigned to unique values not seen in the original dataset, so as to double the vessel traffic as realistically as possible. Additionally, in order to resolve any conflicts due to multiple vessels sharing the same geo-spatial and temporal coordinates, the timestamps on the imputed contacts were offset by 30 minutes. An example of these changes is shown in Tab. 4.12. Note that prefixing "100" maintains the uniqueness over all MMSIs, IMOs, and voyage IDs, all of which were guaranteed to be unique in the original dataset.

Field	Original Contact	Synthetic Contact
MMSI	112358	**100**112358
IMO	99342	**100**99342
Voyage ID	92356ea3-d442-4e01-af8e-ddfae4bf68dc	**100-**92356ea3-d442-4e01-af8e-ddfae4bf68dc
Timestamp	May 14, 2019 17:25:00	May 14, 2019 17:55:00

Table 4.12.: Creating a New AIS Contact

Since each draught value in the original dataset is now present twice in the imputed dataset, the container load through the port is effectively doubled. The same optimization was run on this "doubled" dataset and the resultant fuzzy membership functions are shown in this section.

5. Conclusions and Future Work

5.1. Conclusions

By fusing data from multiple sources, a shipping container damage classification model was built in the first publication to address this problem. This was further improved in a follow-up study, by combining the outputs of multiple classifiers and using some metalearning techniques (in their first documented application to this problem space) to improve the overall prediction accuracy of the classification outcome by 80%. These studies have also resulted in the creation of first documented datasets that may be used in any further investigations. Since the dataset creation methodology is also documented, these datasets can be created and used for similar study by any other research team, globally. To the best of my knowledge, this was the first study in documented literature to investigate shipping container damage and also to apply machine intelligence techniques to this problem.

Criticisms on the robustness of the classification performance due to the presence of some testing data in the training set were addressed and dismissed by experiments using the Leave One Batch Out (LOBO) methodology. Thus, the trained classifiers and the learning methodologies have been shown to be robust against bias in the data and may therefore be deployed on sparser data sets in the future.

These advancements make it possible to determine whether a container will be damaged before it even arrives at the port. Therefore, if a claim were to be filed upon that container, Bruce (from the fictional Port of Miranda) will have already been alerted to it and will not need to follow up on such a claim. Rather, he will simply need to inform the claimant that the container was damaged outside his custody and any action should therefore be taken against other parties.

In order to optimize vessel service time at port, a fuzzy system evolved by a multi-objective genetic algorithm has been created. It has been shown to outperform current industry practice in vessel service time (by almost 80% in some cases) and the amount of resources deployed (by 50% in some cases) to do so. In order to boost the efficacy of this methodology, a new genetic crossover mechanism was developed called FitWAM and applied here for the first time in documented literature. To the best of my knowledge, this was the first study in documented literature to apply a genetically evolved fuzzy system to this problem.

This methodology has also been shown to generalize to multiple geographical regions. Further, the evolved fuzzy systems are able to handle twice the service throughput currently observed in the real-world data without significant additional resource deployment. This supports the claim that this learning methodology yields high performant optimization algorithms that are not constrained by service load or geography, and may thus be deployed to other container ports, globally. In addition, this study has yielded a previously nonexistent data set for future investigations. Finally, filtering vessel locations by port proximity allows for this methodology to be robust against incorrect or incomplete automated messages from vessels increasing its robustness against system and human errors.

These advancements make it possible to operate the Port of Miranda with fewer personnel and at reduced operational costs. This automation also frees personnel from creating, implementing, managing, and executing a resource deployment schedule, further reducing the overhead costs of running the Port of Miranda, even at increased throughput.

These advancements could be incorporated into terminal operating systems (such as Navis N4 [29]) to alert port-side personnel to check specific incoming containers more thoroughly and record any observed damage as they may be predicted to have a higher probability of having an insurance claim filed for. Additionally, such a system could also alert operators at the end of the service of a vessel that their shift is not yet complete.

5.2. Limitations of this Work

The necessity to synthesize parts of the dataset from publicly available information came from the lack of high-veracity data available for this study. This could be improved by forming partnerships with commercial maritime ports and other stakeholders in the supply chain. Such partnerships could yield the container specific data mentioned in Sec. 3.2 as well as the port-side data pertaining to on-shift personnel and internal logs pertaining to delays and container throughput. Container throughput data would eliminate the dependency of this study on the crude mining of this information from AIS data, while internal delay logs would eliminate the need for their synthesis, and allow for higher veracity in extracting meaning from more realistic logs.

The limitations of the computational infrastructure imposed constraints on software packages that could be used in the optimization. As a result, certain techniques (including Petri Nets and multi-output regressors) were not used. The removal of these constraints would afford a broader avenues to explore in the optimization space.

5.3. Future Work

Attempting to apply the same machine learning strategies used to predict shipping container damage, on real-world shipping container damage data (as opposed to approximations thereof) are likely to yield analyses with better veracity that more accurately reflect the real-world benefits of this study. Additional classifier and regression models may also be tested for their viability in this study, and this is left as an avenue of further study.

While advancements in port-side resource deployment have been shown to outperform current industry practice, this was accomplished by evolving only one part of the fuzzy controller. Evolving the fuzzy rule base as well as the membership functions in the defuzzifier may yield a better performing fuzzy system. These are left as avenues of further study.

Further, all natural language processing was limited to keyword searches and pertained only to the English language. More sophisticated natural language processing techniques (perhaps using `word2vec` [99]) may help more accurately read port-side situation reports in order to better tune the fuzzy controller. They may also augment the generalizability of this methodology to ports whose situation reports are not in English. These are left as avenues of further study.

Finally, more real-world data pertaining to the number of containers serviced for each vessel would help improve the veracity of the optimization by eliminating noise from ballast, fuel, etc on board a vessel, eliminating the need to estimate the number of containers from vessel draught.

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A. Shipping Container Damage Prediction Results Data

A.1. Container Damage Claims Classifier Performance Veracity with Leave One One Batch Out Training

A.1.1. Improving Container Damage Claims Classifier Performance Veracity with Leave One One Batch Out Training

Classifier	**Accuracy**	**Precision**	**Recall**
SVM	$0.51 \pm 4.03 \times 10^{-4}$	$0.50 \pm 1.33 \times 10^{-3}$	$0.49 \pm 6.63 \times 10^{-3}$
Naive Bayes	$0.54 \pm 5.76 \times 10^{-17}$	$0.53 \pm 7.46 \times 10^{-17}$	$0.70 \pm 8.26 \times 10^{-17}$
Decision Tree (using $\sqrt{\text{Gini}}$ index)	$0.65 \pm 82 \times 10^{-5}$	$0.64 \pm 7.07 \times 10^{-5}$	$0.70 \pm 1.29 \times 10^{-4}$
Decision Tree (using Information Gain)	$0.66 \pm 8.01 \times 10^{-5}$	$0.64 \pm 7.07 \times 10^{-5}$	$0.68 \pm 1.97 \times 10^{-4}$
AdaBoost (with Naive Bayes)	$0.49 \pm 7.72 \times 10^{-17}$	$0.43 \pm 3.59 \times 10^{-17}$	$0.50 \pm 4.35 \times 10^{-17}$
AdaBoost (with Decision Trees)	$0.65 \pm 2.07 \times 10^{-4}$	$6.38 \pm 2.62 \times 10^{-4}$	$0.70 \pm 2.62 \times 10^{-4}$
Bagging (with Naive Bayes)	$0.54 \pm 2.83 \times 10^{-5}$	$0.53 \pm 2.60 \times 10^{-5}$	$0.70 \pm 2.62 \times 10^{-4}$
Bagging (with Decision Trees)	$0.71 \pm 3.84 \times 10^{-4}$	$0.74 \pm 3.57 \times 10^{-4}$	$0.70 \pm 7.84 \times 10^{-4}$
KNN ($k = 2$)	$0.54 \pm 4.55 \times 10^{-17}$	$0.74 \pm 3.57 \times 10^{-4}$	$0.70 \pm 7.84 \times 10^{-4}$
Random Forest (with 70 $\sqrt{\text{Gini}}$ index Decision Trees)	$0.73 \pm 1.22 \times 10^{-16}$	$0.78 \pm 1.48 \times 10^{-16}$	$0.64 \pm 1.17 \times 10^{-16}$
Random Forest (with 65 Information Gain Decision Trees)	$0.73 \pm 7.34 \times 10^{-17}$	$0.77 \pm 9.83 \times 10^{-17}$	$0.65 \pm 1.21 \times 10^{-16}$

Table A.1.: Performance Metrics of Various Classifiers

Classifier	**Accuracy**	**Precision**	**Recall**
Adaboost (Decision Tree)	$0.73 \pm 1.57 \times 10^{-4}$	$0.72 \pm 2.11 \times 10^{-4}$	$0.74 \pm 1.95 \times 10^{-4}$
Adaboost (Decision Tree InfoGain)	$0.73 \pm 1.31 \times 10^{-4}$	$0.73 \pm 1.90 \times 10^{-4}$	$0.74 \pm 1.76 \times 10^{-4}$
Adaboost (Naive Bayes)	$0.5 \pm 4.76 \times 10^{-4}$	$0.5 \pm 1.41 \times 10^{-3}$	$0.51 \pm 1.11 \times 10^{-2}$
Bagging (Decision Tree)	$0.8 \pm 2.01 \times 10^{-4}$	$0.67 \pm 2.40 \times 10^{-4}$	$0.67 \pm 2.40 \times 10^{-4}$
Bagging (Decision Tree InfoGain)	$0.81 \pm 2.00 \times 10^{-4}$	$0.92 \pm 2.35 \times 10^{-4}$	$0.67 \pm 2.60 \times 10^{-4}$
Bagging (Naive Bayes)	$0.54 \pm 4.32 \times 10^{-4}$	$0.53 \pm 4.46 \times 10^{-4}$	$0.73 \pm 2.16 \times 10^{-3}$
Decision Tree	$0.73 \pm 1.68 \times 10^{-4}$	$0.72 \pm 1.94 \times 10^{-4}$	$0.74 \pm 1.62 \times 10^{-4}$
Decision Tree InfoGain	$0.73 \pm 1.69 \times 10^{-4}$	$0.73 \pm 1.47 \times 10^{-4}$	$0.74 \pm 1.59 \times 10^{-4}$
2-NN	$0.58 \pm 2.88 \times 10^{-04}$	$0.59 \pm 3.54 \times 10^{-4}$	$0.55 \pm 4.67 \times 10^{-4}$
Linear SVM	$0.5 \pm 4.31 \times 10^{-4}$	$0.5 \pm 9.36 \times 10^{-4}$	$0.49 \pm 9.60 \times 10^{-3}$
Mixture of Gaussians	$0.5 \pm 1.67 \times 10^{-4}$	0	0
Naive Bayes	$0.54 \pm 5.94 \times 10^{-4}$	$0.53 \pm 5.70 \times 10^{-4}$	$0.72 \pm 3.97 \times 10^{-3}$
Random Forest (with 10 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 9.16 \times 10^{-5}$	$0.99 \pm 1.27 \times 10^{-4}$	$0.94 \pm 1.44 \times 10^{-4}$
Random Forest (with 2 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.19 \times 10^{-4}$	$0.99 \pm 1.43 \times 10^{-4}$	$0.94 \pm 2.47 \times 10^{-4}$
Random Forest (with 3 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 7.68 \times 10^{-5}$	$0.99 \pm 1.41 \times 10^{-4}$	$0.94 \pm 1.47 \times 10^{-4}$
Random Forest (with 4 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 9.71 \times 10^{-5}$	$0.99 \pm 1.68 \times 10^{-4}$	$0.94 \pm 1.73 \times 10^{-4}$
Random Forest (with 5 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.37 \times 10^{-4}$	$0.99 \pm 1.75 \times 10^{-4}$	$0.94 \pm 1.93 \times 10^{-4}$
Random Forest (with 6 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.12 \times 10^{-4}$	$0.99 \pm 1.60 \times 10^{-4}$	$0.94 \pm 1.35 \times 10^{-4}$
Random Forest (with 7 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.03 \times 10^{-4}$	$0.99 \pm 1.27 \times 10^{-4}$	$0.94 \pm 1.68 \times 10^{-4}$
Random Forest (with 8 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.20 \times 10^{-4}$	$0.99 \pm 1.30 \times 10^{-4}$	$0.94 \pm 1.91 \times 10^{-4}$
Random Forest (with 9 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 9.15 \times 10^{-5}$	$0.99 \pm 1.35 \times 10^{-4}$	$0.94 \pm 1.57 \times 10^{-4}$
Random Forest (with 10 InfoGain Decision Trees)	$0.96 \pm 8.15 \times 10^{-5}$	$0.99 \pm 9.63 \times 10^{-5}$	$0.94 \pm 1.66 \times 10^{-4}$
Random Forest (with 2 InfoGain Decision Trees)	$0.96 \pm 8.74 \times 10^{-5}$	$0.99 \pm 1.39 \times 10^{-4}$	$0.94 \pm 1.62 \times 10^{-4}$
Random Forest (with 3 InfoGain Decision Trees)	$0.96 \pm 1.19 \times 10^{-4}$	$0.99 \pm 1.50 \times 10^{-4}$	$0.94 \pm 2.31 \times 10^{-4}$
Random Forest (with 4 InfoGain Decision Trees)	$0.96 \pm 8.21 \times 10^{-5}$	$0.99 \pm 9.35 \times 10^{-5}$	$0.94 \pm 1.69 \times 10^{-4}$
Random Forest (with 5 InfoGain Decision Trees)	$0.96 \pm 1.06 \times 10^{-4}$	$0.99 \pm 1.42 \times 10^{-4}$	$0.94 \pm 2.00 \times 10^{-4}$
Random Forest (with 6 InfoGain Decision Trees)	$0.96 \pm 9.56 \times 10^{-5}$	$0.99 \pm 1.12 \times 10^{-4}$	$0.94 \pm 1.67 \times 10^{-4}$
Random Forest (with 7 InfoGain Decision Trees)	$0.96 \pm 9.72 \times 10^{-5}$	$0.99 \pm 1.52 \times 10^{-4}$	$0.94 \pm 1.80 \times 10^{-4}$
Random Forest (with 8 InfoGain Decision Trees)	$0.96 \pm 1.00 \times 10^{-4}$	$0.99 \pm 1.08 \times 10^{-4}$	$0.94 \pm 1.75 \times 10^{-4}$
Random Forest (with 9 InfoGain Decision Trees)	$0.96 \pm 1.06 \times 10^{-4}$	$0.99 \pm 1.31 \times 10^{-4}$	$0.94 \pm 2.20 \times 10^{-4}$

Table A.2.: Classifier Performance on the Drop-weather Dataset

Classifier	Accuracy	Precision	Recall
Adaboost (Decision Tree)	$0.73 \pm 4.67 \times 10^{-5}$	$0.73 \pm 6.75 \times 10^{-5}$	$0.74 \pm 5.47 \times 10^{-5}$
Adaboost (Decision Tree InfoGain)	$0.73 \pm 4.41 \times 10^{-5}$	$0.73 \pm 5.75 \times 10^{-5}$	$0.74 \pm 4.40 \times 10^{-5}$
Adaboost (Naive Bayes)	$0.5 \pm 3.64 \times 10^{-4}$	$0.5 \pm 1.77 \times 10^{-3}$	$0.51 \pm 1.08 \times 10^{-2}$
Bagging (Decision Tree)	$0.81 \pm 3.55 \times 10^{-5}$	$0.92 \pm 8.75 \times 10^{-5}$	$0.67 \pm 3.56 \times 10^{-5}$
Bagging (Decision Tree InfoGain)	$0.81 \pm 2.54 \times 10^{-5}$	$0.92 \pm 4.77 \times 10^{-5}$	$0.67 \pm 3.47 \times 10^{-5}$
Bagging (Naive Bayes)	$0.54 \pm 5.72 \times 10^{-5}$	$0.53 \pm 5.61 \times 10^{-5}$	$0.73 \pm 3.67 \times 10^{-4}$
Decision Tree	$0.73 \pm 5.82 \times 10^{-5}$	$0.73 \pm 7.73 \times 10^{-5}$	$0.74 \pm 5.60 \times 10^{-5}$
Decision Tree InfoGain	$0.73 \pm 4.61 \times 10^{-5}$	$0.73 \pm 6.23 \times 10^{-5}$	$0.74 \pm 4.90 \times 10^{-5}$
2-NN	$0.59 \pm 4.61 \times 10^{-5}$	$0.6 \pm 4.65 \times 10^{-5}$	$0.55 \pm 8.86 \times 10^{-5}$
Linear SVM	$0.51 \pm 3.80 \times 10^{-4}$	$0.5 \pm 5.59 \times 10^{-4}$	$0.5 \pm 8.95 \times 10^{-3}$
Mixture of Gaussians	$0.5 \pm 7.54 \times 10^{-6}$	0	0
Naive Bayes	$0.54 \pm 7.06 \times 10^{-5}$	$0.53 \pm 6.61 \times 10^{-5}$	$0.73 \pm 3.90 \times 10^{-4}$
Random Forest (with 10 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.09 \times 10^{-4}$	$0.99 \pm 1.25 \times 10^{-4}$	$0.94 \pm 1.44 \times 10^{-4}$
Random Forest (with 2 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 9.84 \times 10^{-5}$	$0.99 \pm 1.32 \times 10^{-4}$	$0.94 \pm 1.24 \times 10^{-4}$
Random Forest (with 3 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.07 \times 10^{-4}$	$0.98 \pm 1.53 \times 10^{-4}$	$0.94 \pm 1.61 \times 10^{-4}$
Random Forest (with 4 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.45 \times 10^{-4}$	$0.98 \pm 1.59 \times 10^{-4}$	$0.94 \pm 1.85 \times 10^{-4}$
Random Forest (with 5 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.26 \times 10^{-4}$	$0.98 \pm 1.36 \times 10^{-4}$	$0.94 \pm 1.61 \times 10^{-4}$
Random Forest (with 6 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.16 \times 10^{-4}$	$0.99 \pm 1.43 \times 10^{-4}$	$0.94 \pm 1.34 \times 10^{-4}$
Random Forest (with 7 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 8.76 \times 10^{-5}$	$0.98 \pm 1.03 \times 10^{-4}$	$0.94 \pm 1.36 \times 10^{-4}$
Random Forest (with 8 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.55 \times 10^{-4}$	$0.98 \pm 1.70 \times 10^{-4}$	$0.94 \pm 2.02 \times 10^{-4}$
Random Forest (with 9 $\sqrt{Gini}$ Decision Trees)	$0.96 \pm 1.09 \times 10^{-4}$	$0.98 \pm 1.32 \times 10^{-4}$	$0.94 \pm 1.72 \times 10^{-4}$
Random Forest (with 10 InfoGain Decision Trees)	$0.96 \pm 8.20 \times 10^{-5}$	$0.99 \pm 8.51 \times 10^{-5}$	$0.94 \pm 1.35 \times 10^{-4}$
Random Forest (with 2 InfoGain Decision Trees)	$0.96 \pm 1.38 \times 10^{-4}$	$0.99 \pm 1.59 \times 10^{-4}$	$0.94 \pm 1.74 \times 10^{-4}$
Random Forest (with 3 InfoGain Decision Trees)	$0.96 \pm 1.27 \times 10^{-4}$	$0.99 \pm 1.46 \times 10^{-4}$	$0.94 \pm 1.64 \times 10^{-4}$
Random Forest (with 4 InfoGain Decision Trees)	$0.96 \pm 9.88 \times 10^{-5}$	$0.99 \pm 1.20 \times 10^{-4}$	$0.94 \pm 1.38 \times 10^{-4}$
Random Forest (with 5 InfoGain Decision Trees)	$0.96 \pm 1.16 \times 10^{-4}$	$0.99 \pm 1.41 \times 10^{-4}$	$0.94 \pm 1.48 \times 10^{-4}$
Random Forest (with 6 InfoGain Decision Trees)	$0.96 \pm 9.94 \times 10^{-5}$	$0.99 \pm 9.54 \times 10^{-5}$	$0.94 \pm 1.49 \times 10^{-4}$
Random Forest (with 7 InfoGain Decision Trees)	$0.96 \pm 1.06 \times 10^{-4}$	$0.99 \pm 1.29 \times 10^{-4}$	$0.94 \pm 1.69 \times 10^{-4}$
Random Forest (with 8 InfoGain Decision Trees)	$0.96 \pm 1.14 \times 10^{-4}$	$0.99 \pm 1.33 \times 10^{-4}$	$0.94 \pm 1.55 \times 10^{-4}$
Random Forest (with 9 InfoGain Decision Trees)	$0.96 \pm 8.45 \times 10^{-5}$	$0.99 \pm 1.25 \times 10^{-4}$	$0.94 \pm 1.11 \times 10^{-4}$

Table A.3.: Classifier Performance on the LOBO methodology

Classifier	Accuracy	Precision	Recall
Bagging (Decision Tree)	$0.67 \pm 1.04 \times 10^{-2}$	$0.58 \pm 2.67 \times 10^{-2}$	$0.44 \pm 2.53 \times 10^{-2}$
Bagging (Decision Tree InfoGain)	$0.68 \pm 1.10 \times 10^{-2}$	$0.62 \pm 2.77 \times 10^{-2}$	$0.42 \pm 2.09 \times 10^{-2}$
Bagging (Naive Bayes)	$0.49 \pm 9.48 \times 10^{-3}$	$0.4 \pm 1.57 \times 10^{-2}$	$0.69 \pm 1.85 \times 10^{-2}$
2-NN	$0.45 \pm 1.64 \times 10^{-2}$	$0.18 \pm 2.70 \times 10^{-2}$	$0.13 \pm 1.86 \times 10^{-2}$
Random Forest (with 2 $\sqrt{Gini}$ Decision Trees)	$0.88 \pm 1.68 \times 10^{-2}$	$0.89 \pm 2.88 \times 10^{-2}$	$0.75 \pm 3.60 \times 10^{-2}$
Random Forest (with 3 $\sqrt{Gini}$ Decision Trees)	$0.87 \pm 1.63 \times 10^{-2}$	$0.86 \pm 3.12 \times 10^{-2}$	$0.73 \pm 3.88 \times 10^{-2}$
Random Forest (with 4 $\sqrt{Gini}$ Decision Trees)	$0.88 \pm 1.14 \times 10^{-2}$	$0.88 \pm 2.36 \times 10^{-2}$	$0.78 \pm 2.91 \times 10^{-2}$
Random Forest (with 5 $\sqrt{Gini}$ Decision Trees)	$0.87 \pm 1.55 \times 10^{-2}$	$0.88 \pm 2.40 \times 10^{-2}$	$0.72 \pm 3.92 \times 10^{-2}$
Random Forest (with 6 $\sqrt{Gini}$ Decision Trees)	$0.88 \pm 1.38 \times 10^{-2}$	$0.88 \pm 2.87 \times 10^{-2}$	$0.74 \pm 4.08 \times 10^{-2}$
Random Forest (with 7 $\sqrt{Gini}$ Decision Trees)	$0.87 \pm 1.22 \times 10^{-2}$	$0.88 \pm 2.44 \times 10^{-2}$	$0.74 \pm 3.48 \times 10^{-2}$
Random Forest (with 8 $\sqrt{Gini}$ Decision Trees)	$0.86 \pm 1.61 \times 10^{-2}$	$0.86 \pm 1.77 \times 10^{-2}$	$0.74 \pm 4.38 \times 10^{-2}$
Random Forest (with 9 $\sqrt{Gini}$ Decision Trees)	$0.88 \pm 1.19 \times 10^{-2}$	$0.9 \pm 2.50 \times 10^{-2}$	$0.75 \pm 3.11 \times 10^{-2}$
Random Forest (with 10 InfoGain Decision Trees)	$0.87 \pm 1.40 \times 10^{-2}$	$0.89 \pm 2.37 \times 10^{-2}$	$0.71 \pm 3.20 \times 10^{-2}$
Random Forest (with 2 InfoGain Decision Trees)	$0.87 \pm 1.62 \times 10^{-2}$	$0.87 \pm 2.56 \times 10^{-2}$	$0.74 \pm 3.23 \times 10^{-2}$
Random Forest (with 3 InfoGain Decision Trees)	$0.87 \pm 1.49 \times 10^{-2}$	$0.88 \pm 2.24 \times 10^{-2}$	$0.74 \pm 2.90 \times 10^{-2}$
Random Forest (with 4 InfoGain Decision Trees)	$0.87 \pm 1.39 \times 10^{-2}$	$0.88 \pm 3.02 \times 10^{-2}$	$0.75 \pm 3.07 \times 10^{-2}$
Random Forest (with 5 InfoGain Decision Trees)	$0.86 \pm 1.24 \times 10^{-2}$	$0.89 \pm 2.72 \times 10^{-2}$	$0.89 \pm 2.72 \times 10^{-2}$
Random Forest (with 6 InfoGain Decision Trees)	$0.86 \pm 1.33 \times 10^{-2}$	$0.86 \pm 3.28 \times 10^{-2}$	$0.71 \pm 3.46 \times 10^{-2}$
Random Forest (with 7 InfoGain Decision Trees)	$0.88 \pm 1.70 \times 10^{-2}$	$0.87 \pm 2.88 \times 10^{-2}$	$0.75 \pm 4.08 \times 10^{-2}$
Random Forest (with 8 InfoGain Decision Trees)	$0.87 \pm 1.52 \times 10^{-2}$	$0.86 \pm 2.93 \times 10^{-2}$	$0.74 \pm 3.78 \times 10^{-2}$
Random Forest (with 9 InfoGain Decision Trees)	$0.87 \pm 1.30 \times 10^{-2}$	$0.88 \pm 2.69 \times 10^{-2}$	$0.72 \pm 2.96 \times 10^{-2}$

Table A.4.: Classifier Performance on the LOBO Cross Validation Methodology

B. Approval from the Research Ethics Board of the University of Ottawa

uOttawa

FINAL REPORT
Research project

As stipulated in Article 6.14 of the Tri-Council Policy Statement (TCPS 2), researchers must provide a final report for projects that have been approved by the Research Ethics Board (REB). The REB must therefore receive the information requested in this form in order to **close** all REB-approved files.

Name of Principal Investigator (or Supervisor): [redacted] **(Note:** If this is a student project, indicate your supervisor's name)	
Address (Include building name and room number) [redacted]	**Department/School: EECS** **Faculty:Engineering** **E-mail:** [redacted] **Phone:** **Fax:**

Co-investigators and students (4th year, Master's or Doctoral levels)	
Name: [redacted]	**Department/School: EECS**
Address:	**Faculty: Engineering** **E-mail** [redacted] **Phone:** **Fax:**
Name:	**Department/School:**
Address:	**Faculty:** **E-mail:** **Phone:** **Fax:**
Have any team members left or been added to the research team? ☐ Yes ☒ No **If yes, please provide their names, their role in the project and their contact information (for a new member of the research team).**	

Preferred language of correspondence:	☐ **French**	☒ **English**

Ethics File number: H06-17-05	
Title of the research project: Assessing the Causes of Shipping Container Claims	
Initial date of approval: July 13, 2017	
Date of renewal(s) (if applicable): N/A	
Did you receive funding?	☐ Yes ☒ No

Email: [redacted]
Phone: [redacted]

Notice of Collection of Personal Information : Your personal information is collected under the authority of the *University of Ottawa Act* and is indented to be used for the purpose of and those consistent with the administration and the evaluation of the eligibility of your project for ethics approval. If you have any questions regarding this collection of personal information, please contact us by telephone at [redacted] or by email at [redacted]

C. Survey Questions to Maritime Domain Experts

This section presents all the questions posed to domain experts, regarding maritime port operations.

Bottlenecks in Port Operations

Greetings,

My name is Ashwin Panchapakesan and I am a Ph.D. candidate at the University of Ottawa. My work (under the supervision of Dr. Emil Petriu and Dr. Rami Abielmona) focuses on the Process Refinement aspects of Data Fusion, and optimization in general.

My work entails predicting container damage classification in Canadian maritime ports, for which I require knowledge from domain experts such as yourself.

Please rest assured that all your responses are kept confidential (by means of encrypted data storage solutions) and will not be shared with third parties. Any publications resulting from data acquired by this survey will also anonymize yourself and your company.
If it becomes necessary to publish identifying information, that will not be done without first getting your written consent.

I am also willing to sign any Non-Disclosure Agreements (NDAs) that you may deem necessary for data sharing.

This survey should take no more than 30 minutes to complete.
Should you feel the need to do so, you may withdraw from the survey at any point, without any repercussions.
The ethical aspects of this research project have been approved by Research Ethics Board at the University of Ottawa. They may be contacted at 613-562-5387 or by email at [redacted] should you wish to do so, for any reason.
As previously mentioned, my research is performed under the supervision of Dr. Emil Petriu and Dr. Rami Abielmona. Their affiliations and contact information are listed below:

[redacted]
PhD Thesis Supervisor
Professor, University of Ottawa
School of Electrical Engineering and Computer Science
email: [redacted]
website: [redacted]

[redacted]
PhD Thesis Co-Supervisor
V.P. Larus Technologies
Ottawa
email: [redacted]

As a direct consequence of filling out this survey, there are no relevant, foreseeable risks that you may be unaware of, that need to be addressed

Please rest assured that all your responses are kept confidential (by means of encrypted data storage solutions) and will not be shared with third parties

Please note that due to the anonymous nature of this survey, it will be impossible to withdraw data after submission, unless identifying contact information is also provided

Please print and/or save a copy of this consent form for your records

* Required

1. **Do you consent to completing this survey, and would you like to take the survey?** *

   Mark only one oval.

   - Yes *Skip to question 2.*
   - No *Stop filling out this form.*

Bottlenecks in Port Operations

Shipping containers are packed at the port of embarkment and are loaded onto container ships which bring them to your port. A ship's voyage may encounter rough seas and other perils that threaten the safety and fidelity of not only the shipping containers, but also the contents therein. When the shipping container is finally taken to the customer's distribution center, the customer may notice damage sustained by the container and file an intent to claim to your company. At this point, it falls on you to determine whether the damage to the container was sustained while the container was in your custody, or elsewhere.

The investigation required to make this determination is an involved process, as it requires the collation of security video footage of the container as it moved through the premises of your storage yard, and various personnel logs including the various handlers and supervisors who came into contact with this container during this time.

2. **How strongly would you agree with the above statement?**

   Mark only one oval.

   - Strongly disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly agree
   - Not Applicable

Bottlenecks in Port Operations

In order to expedite the process of investigating such claims, it may help to note that containers with certain properties (such as the commercial value of the container's contents, the port of origin, etc) are more likely to be claimed. Please indicate the relevance of such properties.

If you are unsure about any of these questions, please simply ignore them

3. **Who the customer is**

   Mark only one oval.

   - Not relevant at all
   - Somewhat relevant
   - Extremely relevant
   - Not Applicable

4. **The commercial value of goods in container**

   Mark only one oval.

   - Not relevant at all
   - Somewhat relevant
   - Extremely relevant
   - Not Applicable

5. **The port of origin**
Mark only one oval.
- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

6. **The shipping line**
Mark only one oval.
- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

7. **The weather at the port of origin**
Mark only one oval.
- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

8. **The weather and sea state along the ship's voyage to your port**
Mark only one oval.
- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

9. **The fragility of the goods in the shipping container**
Mark only one oval.
- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

10. **The season (fall/winter/spring/summer) when the container was packed**
Mark only one oval.
- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

11. **The season (fall/winter/spring/summer) when the container was loaded onto the ship**
Mark only one oval.

- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

12. **The amount of time the container spent in your storage yard before it was picked up for delivery to the customer (at their distribution center, warehouse, etc)**
Mark only one oval.

- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

13. **The presence of hazardous material in the container**
Mark only one oval.

- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

14. **The trucking company that picked up the container from your storage yard and delivered it to the customer**
Mark only one oval.

- Not relevant at all
- Somewhat relevant
- Extremely relevant
- Not Applicable

15. **Are there any other properties that you feel I may have missed?**
Mark only one oval.

- Yes *Skip to question 16.*
- No *Skip to question 19.*

Additional Properties

16. **Please list a property of a container that makes it more likely to be claimed**

17. **Please indicate the relevance of this property**
Mark only one oval.

- Not relevant at all
- Somewhat relevant
- Extremely relevant

18. **Would you like to list another property?**
Mark only one oval.

- Yes *Skip to question 16.*
- No *Skip to question 19.*

Prediction Accuracy

19. **Given the relevance of these properties in inducing shipping container damage claims, do you try to predict which containers may be damaged (and therefore claimed) before the claim is submitted to you?**
Mark only one oval.

- Yes *Skip to question 20.*
- No *Skip to question 24.*

Prediction Accuracy

You had indicated that you try to predict which containers may be damaged (and therefore claimed) before the claim is submitted to you.

20. **How accurate are your predictions?**
Mark only one oval.

- We do not predict
- 0-25% accurate
- 25-50% accurate
- 50-75% accurate
- 75-100% accurate
- Not Applicable

21. **How long (in person hours) on average would you say it takes for a human operator to gather all the relevant data about a claim BEFORE the claim is made by the customer?**

22. **How long (in person hours) on average would you say it takes for a human operator to gather all the relevant data about a claim AFTER the claim is made by the customer?**

23. **How long (in person hours) on average would you say it takes for all the relevant data about a claim to be collected, collated and analyzed, before a decision is made?**

Information Collection

When a claim does occur, the collection and collation of the necessary information (security video footage, personnel logs, etc) are the longest and most involved processes, causing a bottleneck in the decision-making process.

24. **How strongly would you agree with this statement?**
    Mark only one oval.
    - Strongly disagree
    - Somewhat disagree
    - Neither agree nor disagree
    - Somewhat agree
    - Strongly agree
    - Not Applicable

Fantuzzis

Do you use Fantuzzis or similar equipment (forklifts with spreaders) within the port?

25. **Do you use Fantuzzis or similar equipment (forklifts with spreaders) within the port?**
    Mark only one oval.
    - Yes *Skip to question 26.*
    - No *Skip to question 29.*

Fantuzzi Questions

You had indicated that you use Fantuzzis or similar equipment in your terminal

26. **How many operators for such equipment are typically working at your terminal at any given point in time?**

27. **Would you agree that there is a correlation between claims for damaged containers and the operators of the Fantuzzi equipment that handled such containers?**
    Mark only one oval.
    - Yes *Skip to question 28.*
    - No *Skip to question 29.*

Fantuzzi Correlation

You had indicated that there is a correlation between claims for damaged containers and the operators of the Fantuzzi equipment that handled such containers.

28. **Please indicate the strength and the direction of this correlation**
Mark only one oval.

- An increase in the number of containers handled by a given Fantuzzi operator often results in a decrease in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers handled by a given Fantuzzi operator sometimes results in a decrease in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers handled by a given Fantuzzi operator results in no significant/noticeable increase or decrease in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers handled by a given Fantuzzi operator sometimes results in an increase in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers handled by a given Fantuzzi operator often results in an increase in the number damaged/claimed containers transported by that shipping line

Shipping Lines

29. **How strongly would you agree with the claim that there is a correlation between shipping lines and container damage/claims (i.e. a shipping line whose containers are more likely to be claimed for damage)?**
Mark only one oval.

- Strongly disagree *Skip to question 36.*
- Somewhat disagree *Skip to question 36.*
- Neither agree nor disagree *Skip to question 36.*
- Somewhat agree *Skip to question 30.*
- Strongly agree *Skip to question 30.*
- Not Applicable *Skip to question 36.*

Shipping line correlation

You had indicated that there is a correlation between shipping lines and container damage/claims

30. **Please indicate the strength and direction of this correlation**
Mark only one oval.

- An increase in the number of containers transported by a given shipping line often results in a decrease in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers transported by a given shipping line sometimes results in a decrease in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers transported by a given shipping line results in no significant/noticeable increase or decrease in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers transported by a given shipping line sometimes results in an increase in the number damaged/claimed containers transported by that shipping line
- An increase in the number of containers transported by a given shipping line often results in an increase in the number damaged/claimed containers transported by that shipping line

31. **Please indicate which shipping lines have strong negative correlations in this respect**

32. **Please indicate which shipping lines have weak negative correlations in this respect**

33. **Please indicate which shipping lines have neutral correlations in this respect**

34. **Please indicate which shipping lines have weak positive correlations in this respect**

35. **Please indicate which shipping lines have strong positive correlations in this respect**

Trucking Companies

36. **How strongly would you agree with the claim that there is a correlation between trucking companies and container damage/claims (i.e. a trucking company whose containers are more likely to be claimed for damage)?**

Mark only one oval.

- Strongly disagree *Skip to question 38.*
- Disagree *Skip to question 38.*
- Neutral *Skip to question 38.*
- Agree *Skip to question 37.*
- Strongly agree *Skip to question 37.*
- Not Applicable *Skip to question 38.*

Trucking Company Correlation

You had indicated that there is a correlation between trucking companies and container damage/claims (i.e. a trucking company whose containers are more likely to be claimed for damage)

37. **Please indicate the strength and direction of this correlation**

Mark only one oval.

- An increase in the number of containers transported by a given trucking company often results in a decrease in the number damaged/claimed containers transported by that trucking company
- An increase in the number of containers transported by a given trucking company sometimes results in a decrease in the number damaged/claimed containers transported by that trucking company
- An increase in the number of containers transported by a given trucking company results in no significant/noticeable increase or decrease in the number damaged/claimed containers transported by that trucking company
- An increase in the number of containers transported by a given trucking company sometimes results in an increase in the number damaged/claimed containers transported by that trucking company
- An increase in the number of containers transported by a given trucking company often results in an increase in the number damaged/claimed containers transported by that trucking company

Cargo Types

38. **How strongly would you agree with the claim that there is a correlation between cargo types and container damage/claims (i.e. containers holding a certain type of cargo, say farm equipment, are more likely to be claimed for damage)?**

Mark only one oval.

- Strongly disagree *Skip to question 40.*
- Disagree *Skip to question 40.*
- Neutral *Skip to question 40.*
- Agree *Skip to question 39.*
- Strongly agree *Skip to question 39.*
- Not Applicable *Skip to question 40.*

Cargo Types Correlation

You had indicated that there is a correlation between cargo types and container damage/claims (i.e. containers holding a certain type of cargo, say farm equipment, are more likely to be claimed for damage).

39. **Please elaborate on which cargo types tend to be associated with a higher probability of container damage/claims.**

Gantry Crane

40. **How strongly would you agree with the claim that there is a correlation between the ship-to-shore gantry crane operator and container damage/claims (i.e. containers handled by a specific gantry crane operator are more likely to be claimed for damage)?**
Mark only one oval.

- Strongly disagree *Skip to question 42.*
- Disagree *Skip to question 42.*
- Neutral *Skip to question 42.*
- Agree *Skip to question 41.*
- Strongly agree *Skip to question 41.*
- Not Applicable *Skip to question 42.*

Gantry Crane Correlation

You had indicated that there is a correlation between the ship-to-shore gantry crane operator and container damage/claims (i.e. containers handled by a specific gantry crane operator are more likely to be claimed for damage).

41. **Please indicate the strength and direction of this correlation**
Mark only one oval.

- An increase in the number of containers transported by a given gantry crane operator often results in a decrease in the number damaged/claimed containers transported by that gantry crane operator
- An increase in the number of containers transported by a given gantry crane operator sometimes results in a decrease in the number damaged/claimed containers transported by that gantry crane operator
- An increase in the number of containers transported by a given gantry crane operator results in no significant/noticeable increase or decrease in the number damaged/claimed containers transported by that gantry crane operator
- An increase in the number of containers transported by a given gantry crane operator sometimes results in an increase in the number damaged/claimed containers transported by that gantry crane operator
- An increase in the number of containers transported by a given gantry crane operator often results in an increase in the number damaged/claimed containers transported by that gantry crane operator

Shunt Truck

42. **How strongly would you agree with the claim that there is a correlation between the shunt truck operator and container damage/claims (i.e. containers handled by a specific shunt truck operator are more likely to be claimed for damage)?**
Mark only one oval.

- Strongly disagree *Skip to question 44.*
- Disagree *Skip to question 44.*
- Neutral *Skip to question 44.*
- Agree *Skip to question 43.*
- Strongly agree *Skip to question 43.*
- Not Applicable *Skip to question 44.*

Shunt Truck Correlation

You had indicated that there is a correlation between the shunt truck operator and container damage/claims (i.e. containers handled by a specific shunt truck operator are more likely to be claimed for damage).

43. **Please indicate the strength and direction of this correlation**
Mark only one oval.

- An increase in the number of containers transported by a given shunt truck operator often results in a decrease in the number damaged/claimed containers transported by that shunt truck operator
- An increase in the number of containers transported by a given shunt truck operator sometimes results in a decrease in the number damaged/claimed containers transported by that shunt truck operator
- An increase in the number of containers transported by a given shunt truck operator results in no significant/noticeable increase or decrease in the number damaged/claimed containers transported by that shunt truck operator
- An increase in the number of containers transported by a given shunt truck operator sometimes results in an increase in the number damaged/claimed containers transported by that shunt truck operator
- An increase in the number of containers transported by a given shunt truck operator often results in an increase in the number damaged/claimed containers transported by that shunt truck operator

Container Weight

44. **How strongly would you agree with the claim that there is a correlation between the weight of the container (including the weight of the cargo it contains) and container damage/claims (i.e. containers that fall within certain weight ranges are more likely to be claimed for damage)?**

Mark only one oval.

- Strongly disagree *Skip to question 46.*
- Somewhat disagree *Skip to question 46.*
- Neither agree nor disagree *Skip to question 46.*
- Somewhat agree *Skip to question 45.*
- Strongly Agree *Skip to question 45.*
- Not Applicable *Skip to question 46.*

Container Weight Correlation

You had indicated that there is a correlation between the weight of the container (including the weight of the cargo it contains) and container damage/claims (i.e. containers that fall within certain weight ranges are more likely to be claimed for damage).

45. **please elaborate on which weight ranges tend to be associated with a higher probability of container damage/claims.**

Ship Piloting Procedure

46. **When a ship encounters a wave while at sea, is there a recommended or conventional procedure describing the angle at which the ship should approach the wave? I.e. should it always travel parallel/perpendicular to the wave, or should it always approach the wave at a 45 degree angle? or should it change its approach angle based on the height of the wave, and the size and the weight of the ship?**

Additional Comments

Please leave any additional comments that you feel may help me out

Contact

47. **May I contact you for additional clarifications on your responses in this survey?**
Mark only one oval.

- Yes *Skip to question 48.*
- No *Skip to "Thank You."*

Contact Information

48. **Please provide information about how you'd prefer to be contacted**

Thank You

Thank you for taking the time to answer the survey. I really do appreciate it