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THESIS

EFFECTS OF EXTENDED-RANGE FORECASTING IN AUTOMATED SHIP ROUTING

by

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June 2023

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**EFFECTS OF EXTENDED-RANGE FORECASTING IN AUTOMATED SHIP
ROUTING**

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ABSTRACT

Development of the Navy Earth System Prediction Capability (ESPC) has improved the accuracy of extended-range environmental forecasting. However, the effects of using this capability in ship routing are not known. The Naval Research Laboratory (NRL) has developed a tool, the Tool for Multi-objective PLanning and Asset Routing (TMPLAR), to optimize ship routes while considering objectives including time, fuel costs, and environmental conditions. This thesis reports a simulation experiment using recent ESPC forecasts and forecasts from a legacy forecasting system in TMPLAR. ESPC impact on ship routes and their fuel consumption, overall transit times, and exposure to waves is explored. Our findings are inconclusive regarding ESPC performance against the legacy and climatology forecasting systems. However, large-scale simulation has drastically improved TMPLAR robustness and provided useful insight into overall TMPLAR behavior at a significantly reduced cost relative to any real-world experiment.

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LIST OF ACRONYMS AND ABBREVIATIONS

ACAF	Advanced Climate Analysis and Forecasting
CICE	Community Ice CodE
CLF	Combat Logistics Force
CSV	comma-separated values
DOD	Department of Defense
DOE	design of experiments
DTG	date time group
ECMWF	European Centre for Medium-Range Weather Forecasts
ESPC	Earth System Prediction Capability
FNMOC	Fleet Numerical Meteorology and Oceanography Center
FY	fiscal year
GODAE	Global Ocean Data Assimilation Experiment
HYCOM	HYbrid Coordinate Ocean Model
JSON	JavaScript Object Notation
KML	Keyhole Markup Language
METOC	meteorological and oceanographic
NAVGEN	NAVy Global Environmental Model
NCEP	National Centers for Environmental Prediction
NIST	National Institute of Standards and Technology
NOAA	National Oceanic and Atmospheric Administration
NOLH	Nearly Orthogonal Latin Hypercube
NOPP	National Ocean Partnership Program
NRL	Naval Research Laboratory
NTSB	National Transportation Safety Board
OTSR	optimum track ship routing
RASP	Replenishment at Sea Planner
STARS	Ship Track and Routing System
SVP	Smart Voyage Planning
TMPLAR	Tool for Multi-objective Planning and Asset Routing
U.S.	United States

UCONN	University of Connecticut
VBM	vertical bending moment
WWIII	Wave Watch III

EXECUTIVE SUMMARY

Development of the Navy Earth System Prediction Capability (ESPC) has improved the accuracy of extended-range environmental forecasting. However, the effects of using this capability in ship routing are not known. The Naval Research Laboratory (NRL) has developed a tool, the Tool for Multi-objective PLanning and Asset Routing (TMPLAR), to optimize ship routes while considering objectives including time, fuel costs, and environmental conditions. This thesis reports a simulation experiment using recent ESPC forecasts and forecasts from a legacy forecasting system in TMPLAR. ESPC impact on ship routes and their fuel consumption, overall transit times, and exposure to waves is explored. Thus, this research seeks to answer the following question: **Does the Navy's new ESPC improve routes generated by TMPLAR relative to other forecast models?**

We approach the problem via data farming and simulation analysis, using historical forecasts, TMPLAR, and a carefully designed experiment. Once TMPLAR generates routes, we collect outcomes including fuel consumption, measured in thousands of gallons; route duration, measured in hours; and maximum wave heights experienced by ships during route execution, measured in feet. We compare legacy forecast systems, which consist of NAVy Global Environmental Model (NAVGEM), Wave Watch III (WWIII), and HYbrid Coordinate Ocean Model (HYCOM), and climatology. Summary statistics and visualization tools are used to extract meaningful insight on the effects of ESPC on various objective function values produced by TMPLAR.

We conclude that more research is required to answer our research question. TMPLAR outputs between forecasting systems tend to be more variable the more distant port origins and destinations are from one another. On average, we see ESPC routes using more fuel, requiring less time, and experiencing similar wave conditions as our legacy and climatology routes. However, the variability of our outputs is significant, and more research is required to determine the causes of such variability.

The most significant contribution this research provides is insight into overall TMPLAR behavior. First, single-objective routing in TMPLAR for fuel minimization is

not recommended for military operations that are time sensitive. We see significant fuel savings when fuel is minimized vice time/distance, but our desired arrival time windows are not honored. Second, TMPLAR is highly sensitive to port coordinates that are close to land. Planners may have to adjust port locations further offshore for TMPLAR to successfully run. Third, when constructing routes with replanning disabled, routes are almost always identical, regardless of which forecasting system is used. It is only when replanning is enabled that we see variability in TMPLAR outputs. Finally, TMPLAR is not exempt from the dangers of routing with outdated METOC information. Our simulation revealed a scenario where a ship was routed into rough sea states due to outdated environmental forecast information. Planners should be aware of the potential hazards they face when routing with outdated environmental forecasts.

The value of simulation in reaching these conclusions cannot be understated. A real-world, large-scale experiment with TMPLAR would come at a great cost in terms of time and money. Learning these lessons in actual fleet operations could be dangerous as well, depending on the environmental conditions faced by actual ships. While our results regarding ESPC performance in TMPLAR are inconclusive, the value gained in improving TMPLAR robustness is significant.

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I. INTRODUCTION

A. PROBLEM STATEMENT

The United States (U.S.) Navy is responsible for the security of the sea domain for the U.S. and its allies. As of January 4, 2023, the U.S. Navy's ship battle force consists of 293 commissioned vessels (Naval Vessel Register 2023). Given the vast size of the sea domain and the U.S. Navy's limited number of assets, naval vessels must travel vast distances to meet mission requirements. Per the Operational Energy Report for fiscal year (FY) 2020, the Department of Defense (DOD) spent \$9.2 billion on 78 million barrels of fuel (Office of the Under Secretary of Defense for Acquisition and Sustainment 2021). The same report outlines that the U.S. Navy is responsible for 36 percent of this fuel usage, or roughly \$3.3 billion. The report goes further in depth and determines that of this amount, approximately 32 percent is consumed by surface ships, or roughly \$1 billion. It is advantageous for the U.S. Navy to reduce this cost as much as possible so money can be invested elsewhere. Most importantly, saving fuel improves operational endurance. One way to reduce ship fuel consumption and cost is through efficient voyage routing. That is, getting ships to their destinations in the most efficient manner.

A common approach is to route ships via the great circle distance, which is the shortest path between two points. However, this is not always feasible. Natural and artificial obstacles, environmental conditions, ship capabilities, and resource limitations can make routing naval vessels via the great circle distance impractical around the globe. If we route ships without these considerations, we run the risk of sending ships into various obstacles, dangerous weather conditions, or impassable sea states. The sinking of the U.S. cargo vessel El Faro illustrates what can happen if environmental conditions are not properly considered. On September 29, 2015, El Faro left Jacksonville, Florida, with a destination of San Juan, Puerto Rico. At the time of departure, there was a tropical storm in the vicinity of their path, but current weather conditions at the time were still permissive for departure. By September 30, the storm grew to hurricane strength, with the given name Joaquin. Using a weather forecasting system that communicated information that was six hours old and delivered only via email, the captain remained confident of the general course

(National Transportation Safety Board 2017). That is, only slight deviations were made to the original planned route at departure as shown in Figure 1.



Figure 1. Path of El Faro. Source: National Transportation Safety Board (2017)

This would prove to be catastrophic, as the wind conditions and sea states caused massive flooding and engine failure, which eventually led to the sinking of the ship and deaths of 33 individuals on October 1 (National Transportation Safety Board 2017). The National Transportation Safety Board (NTSB) concluded that several factors contributed to the sinking, including the use of non-current weather information. This accident shows the importance of having accurate meteorological and oceanographic (METOC) information in route construction.

Optimum track ship routing (OTSR) is the process of constructing “optimal” ship routes while considering additional factors such as environmental conditions, ship capabilities and other real-world constraints. How we define “optimal” ultimately depends on our mission objectives. A few examples may include transit time minimization or fuel consumption minimization. The U.S. Navy does not currently rely on OTSR automation in route construction. The process used today involves a team of leaders hand planning a route via great circle distance in conjunction with climatology information, generally out to the

one-to-five-day range, with weather verification being done post route construction (Jacques 2023). That is, once a route is constructed, leaders will verify permissibility by cross-referencing it with various METOC forecasting systems used by the U.S. Navy.

What if route planners had a tool that could automate route construction between two points with the objective of minimizing things like time, distance, and fuel consumption? Additionally, what if these automation tools could pull METOC data to verify that weather conditions are permissive along such route? Algorithms have been developed for research purposes to study this opportunity. The Ship Track and Routing System (STARS) and Tool for Multi-objective Planning and Asset Routing (TMPLAR) are two OTSR algorithms that construct efficient routes with METOC considerations. This study explores METOC forecasting system performance using TMPLAR for route optimization.

The TMPLAR algorithm can incorporate wind, wave, and current information in route construction. This information can be sourced from several alternative sources, including climatology, legacy systems such as the NAVy Global Environmental Model (NAVGEN), Wave Watch III (WWIII) and HYbrid Coordinate Ocean Model (HYCOM), as well as more advanced forecasting systems, such as the Navy Earth System Prediction Capability (ESPC). Research has not yet been conducted on how each forecasting system compares to one another in terms of the routes constructed within TMPLAR. The focus of this research is on how the U.S. Navy's most advanced forecasting system, known as ESPC, performs relative to legacy forecasting systems and climatology. Note that when we refer to "legacy" forecasting systems in various sections of this study, we are referring to NAVGEN, WWIII, and HYCOM.

Extended-range forecasting, as provided by ESPC, has the potential to provide decision makers with the ability to conduct extend-range planning. It is important to identify what the potential costs and cost savings are so that decision makers can weigh risks in planning.

Conducting an observational study on Navy ESPC and its effect on various objectives, such as time, distance traveled, and fuel consumption, would come at a

significant cost in many domains. It would not be feasible to take military vessels away from operational commitments and expend fuel resources to conduct a real-world study. Furthermore, collecting observational data takes time and it is unknown how much data would be required to detect potential influences on variability of multiple outcomes. Therefore, an alternative method of study is required.

Large scale simulation and its capabilities have advanced rapidly and continue to improve as computing systems become more powerful. Advantages of simulation compared to real world experiments include cost, safety, and flexibility (Sanchez et al. 2017). This thesis reports an experiment using a space filling design to select settings including environmental forecasts, and running these with TMPLAR, to extract information about the routes that are constructed.

B. IMPACT OF METOC ON ROUTE PLANNING AND PERFORMANCE

There are many studies involving OTSR and the incorporation of weather. However, there is limited research that directly focuses on how weather affects routing specifically with the OTSR automation tools developed by the U.S. Navy. Hall (2012) conducted sensitivity analysis on routes generated from STARS and analyzed them for robustness. A key takeaway from her analysis is that the routes generated by STARS tend to be robust to varying environmental conditions. That is, for the most part, routes generated were not sensitive to environmental conditions. Additionally, her analysis suggested that location and time of year have a significant impact on how environmental conditions affect routing.

Lantz (2014) added the anticipated positions of tropical cyclones to the Replenishment at Sea Planner (RASP) for the U.S. Navy. The Combat Logistics Force (CLF) uses RASP to produce resupply schedules up to 45 days in advance. At the time of publication, RASP did not consider weather phenomena when constructing these schedules and routes. The results of his study suggest that the relative positions of tropical cyclones should be represented as a 24-hour forecast when running RASP. Using current storm locations put ships at risk of being routed directly into storms. Using three-day forecasts resulted in ships being routed much farther than necessary to avoid storms.

Chu et al. (2014) studied meteorology in the Smart Voyage Planning (SVP) tool. SVP is a commercial product that can incorporate METOC models and forecasts to reduce the overall carbon emissions of a voyage. The study concluded that location, bearing, seasonal weather patterns, hull characteristics, propulsion capabilities, route length, and other model improvements were all factors to which SVP was highly sensitive.

The literature suggests that OTSR algorithms are highly sensitive to location, route length, and time of year. These themes play a role in our experiment. Design points were selected in our experiment with enough variability to capture a wide range of route possibilities in the real world. We also learned that forecast update frequency plays a role in final route optimization outputs. Accordingly, this is a factor that we vary in our experiment.

C. RESEARCH APPROACH

The effects of using extended-range forecasting in ship routing algorithms is not yet known. Specifically, the effects of using Navy ESPC in TMPLAR have not been thoroughly researched. This research seeks to address the following question: **Does the Navy's new ESPC improve routes generated by TMPLAR relative to other forecast models?**

We utilize large scale simulation experiments to compare Navy ESPC with other forecast models. Specifically, we construct a space filling design of experiments (DOE) to select various parameters for TMPLAR ingestion. We pass these input parameter combinations into TMPLAR and record the output data. After data cleaning and preparation, we use summary statistics and visualization tools to assess the sensitivity of the outputs to the input factors and perform robustness analysis on extended-range forecasting with varying objectives.

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II. AUTOMATED SHIP ROUTING

A. OLDER AUTOMATED ROUTING SYSTEMS

STARS is an older ship routing software tool provided by the Fleet Numerical Meteorology and Oceanography Center (FNMOC) and used by the Naval Research Laboratory (NRL) in Monterey (Miller 2012). STARS uses a single objective (power) cost function that it seeks to minimize when constructing routes. Fuel consumption and distance make up the power function (Sidoti et al. 2016). The routes produced consist of waypoints between the origin and destination, and are completed within the user-selected time limits while considering fuel minimization and wind and sea exposure (Miller 2012).

STARS is now obsolete and has been replaced by TMPLAR for OTSR automation research purposes at NRL (Sidoti 2023a). TMPLAR has the unique advantage of multi-objective optimization and has outperformed STARS in previous studies (Sidoti et al. 2016). See Figure 2 as an example.

Scenario		STARS++		TMPLAR	
Origin	Destination	Fuel	Distance	Fuel	Distance
Alaska	San Diego	143.7	2187	103.9	1937
Alaska	Seattle	95.80	923.4	61.24	965.2
Guam	Sasebo	133.7	1255	93.64	1360
Norfolk	Haiti	96.00	964.9	38.33	880.8
Gibraltar	Norfolk	282.5	3466	255.2	3429
New Orleans	Venezuela	—	—	146.0	1951

All fuel consumption measured in thousands of gallons.
All distances measured in nautical miles.

Figure 2. STARS vs. TMPLAR Performance. Source: Sidoti et al. (2016)

In Sidoti et al.'s article, Multiobjective Path-Planning Algorithm With Time Windows For Asset Routing, we see TMPLAR outperforming STARS on average by 1.7% in regards to

distance traveled and 33% in fuel consumption. It is for these reasons that we have chosen to conduct our research using the TMPLAR algorithm.

B. TMPLAR

TMPLAR was developed by the University of Connecticut (UConn) and NRL to route vessels in an efficient manner while considering additional, dynamic, and real-world constraints. Like STARS, TMPLAR routes consist of waypoints with associated arrival and departure times, speeds, and bearings, and can be optimized based on single or several objectives (Sidoti et al. 2016). That is, users can select optimize routes based on single or multiple objectives, such as time, distance traveled, fuel consumption, and environmental exposures.

Additional considerations in TMPLAR include sea depth calculations to ensure a route is feasible for a specified vessel. This bathymetry data is extracted from the Oceanographic Atmospheric Master Library from NRL in Monterey, CA, as well as the Stennis Space Center, and is divided into four groups: shallow water, water deeper than a specified threshold, land, and unknown (Sidoti et al. 2016). Most important, ships can be routed using historical climatology data, current weather conditions, or weather forecasts from various naval systems and models.

The algorithm itself is written in Python coding language version 3.6. The program ingests what we will refer to as “input payloads,” which contain the various user-selected constraints for route construction. The input payloads are in JavaScript Object Notation (JSON) format. An example can be seen in Figure 3.

```

{
  "endDtg": "2021-01-01T09:30:00.000Z",
  "lateArrivalHrs": 60,
  "earlyArrivalHrs": 66,
  "startDtg": "2020-12-20T00:00:00.000Z",
  "speed": 16,
  "maxSpeed": 32,
  "minSpeed": 1,
  "settings": {
    "openWater": "false",
    "numOfCOAs": 1,
    "algorithm": "1",
    "mode": "replan",
    "globalQuad": "true",
    "updateFreq": 336
  },
  "objectives": [
    "time"
  ],
  "origin": {
    "geomWkt": "POINT (151.261 -34.017)",
    "pimDtg": "2020-12-20T00:00:00.000Z"
  },
  "destination": {
    "geomWkt": "POINT (129.054 35.039)",
    "pimDtg": "2021-01-01T09:30:00.000Z"
  },
  "waypoints": [],
  "windModel": "NAVGEN",
  "waveModel": "WW3_GLOBAL",
  "currModel": "HYCOM_GLOBAL",
  "surfaceParams": {
    "shipName": "Ship Name",
    "shipClass": "DDG51",
    "shipForwardDraft": 11.7,
    "shipAftDraft": 12,
    "shipTransvGM": 2.6,
    "maxHeadSea": 12,
    "maxBeamSea": 12,
    "maxFollowingSea": 12,
    "maxTrueWind": 35,
    "maxRelWind": 35
  }
}

```

Figure 3. Example TMPLAR Input Payload

In our example in Figure 3, we seek a route from Sydney, Australia, to Busan, South Korea, as specified in the “origin” and “destination” keys in longitude/latitude format. Our requested date of departure, found in “startDtg” and “pimDtg,” and arrival dates, found in “endDtg” and “pimDtg,” are entered in ISO 8601 format. The “earlyArrivalHrs” and “lateArrivalHrs” keys represent user-selected flexibility in arrival time. That is, the number of permissible hours one can arrive early or late at the destination. Three speed parameters are also available for user selection. Our “speed” key represents our average cruising speed desired and our “min/maxSpeed” keys cover the range of speed we want to operate within. The “settings” keys allow users to adjust default administrative settings within the algorithm. Note that our “mode” and “updateFreq” parameters are the only keys varied in

the “settings” section. When “mode” is set to “normal,” no route updates will take place during route execution. When “mode” is set to “replan,” route adjustments can be made while underway using updated forecasting information at a frequency set by the “updateFreq” key. In this example, new information is pulled every two weeks (336 hours), which may be relevant depending on the duration of the route. Our “objectives” key is where we input what we want minimized. In the example in Figure 3, we seek to minimize our time of transit. Other options may include fuel, distance, and environmental exposures. If there are any desired stops along a route, users can input these locations under “waypoints.” We will not be adding any stops between origin/destination pairs in our experiment. Weather forecasting systems are selected in the “wind/wave/currentModel” keys. In the Figure 3 example, we are using the legacy forecasting systems. Finally, our “surfaceParams” key allows users to select what type of vessel is being routed. This information is important for fuel consumption estimation, overall ship capabilities, and ship resilience to inclement weather conditions. Furthermore, users can input maximum thresholds for environmental exposure of the ship. Note that for all experiments in this study, only DDG-51 Guided Missile Destroyer information was used. This was the only ship class for which NRL possessed complete ship data. Efforts are being made to construct complete data sets on additional ship classes (Sidoti 2023b).

TMPLAR output files are also in JSON format and contain a litany of information about the route recommendation. The route is broken down into a series of waypoints between the origin and destination. At each waypoint, location, course direction, objective function values attributed to the previous leg, cumulative objective function values, and additional information pertaining to the ship are recorded. Ship information includes elements such as speed, acceleration, roll, pitch, and vertical bending moment (VBM). Additionally, any errors encountered in the algorithm are recorded for user awareness. With these output files, we can easily pull the cumulative objective function values at our destination waypoint.

III. METOC FORECASTING SYSTEMS

A. BACKGROUND

Almost every mission the U.S. Navy and Marine Corps conducts is affected by METOC conditions. It is relevant in areas such as submarine warfare, special warfare, ordnance disposal, ground warfare, aviation, and surface warfare. Leaders use METOC information to help guide ships, aircraft, and troops, pass forecasting information to military and civilian authorities, prepare charts for search and rescue operations, and much more (United States Naval Academy 2023). Various METOC forecasting systems are used to meet the needs of various warfare domains.

B. METOC SYSTEMS USED IN EXPERIMENT

Three environmental variables can be used in route construction with TMPLAR: winds, waves, and currents. This study focuses on wave information, given that fuel consumption rates are calculated with wave data only (Sidoti 2023c). Additionally, given various hurdles of transferring ESPC data to NRL, only ESPC wave data could be acquired from FNMOC in Monterey, California. Thus, when we refer to ESPC in this study, note that we are still using the NAVGEM weather prediction system for wind forecasts and the HYCOM for current conditions, as summarized in Table 1.

Table 1. METOC Forecasting Systems for Simulation

	Climate	Legacy	ESPC
windModel	CLIMO	NAVGEM	NAVGEM
waveModel	CLIMO	WW3_GLOBAL	ESPC
currModel	CLIMO	HYCOM_GLOBAL	HYCOM_GLOBAL

C. CLIMATOLOGY

Climatology data was provided by FNMOC in Monterey, California using the Advanced Climate Analysis and Forecasting (ACAF) tool. Data reflects the long-term

means of METOC conditions reported in various forecasting systems. For our design, climatology data was gathered from multiple reanalysis datasets. Our areas of interest were global to ensure maximum data presence for our ship routes.

D. LEGACY

Wind information for our legacy system is pulled from NAVGEM. NAVGEM is run by FNMOC in Monterey, California, as well (Hogan et al. 2014). Per Hogan et al., first generation NAVGEM systems can provide high-resolution, 180-hour global forecasts with multiple updates per day. The authors also explain that hundreds of thousands of global products are produced every day and used across many DOD organizations. A few examples provided include NAVGEM data being used in WWIII ocean wave models as well as HYCOM. This data includes information about surface pressure, winds, temperature, humidity, and clouds. The NAVGEM data we use in our experiment has a maximum forecast range of 180 hours over six-hour intervals, with an update frequency of every 12 hours.

Wave information is pulled from WWIII. WWIII was developed at the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Prediction (NCEP) and uses information about wave height, water depth, and currents to solve the random phase spectral action density balance equation (National Weather Service 2023). Similarly to NAVGEM, our WWIII forecasts are updated every 12 hours and have six-hour intervals. Note that we use the deterministic WWIII model, thus our maximum forecasting range is 180 hours. That is, the deterministic model reflects ensemble mean forecasts without any notion of variability.

Lastly, our ocean current information is pulled from HYCOM. HYCOM is a data-assimilative hybrid isopycnal-sigma-pressure (generalized) coordinate ocean model developed by multiple institutions (HYCOM 2023). Per the hycom.org website, HYCOM development and evaluation is sponsored by the National Ocean Partnership Program (NOPP) as part of the U. S. Global Ocean Data Assimilation Experiment (GODAE). The website also discusses how several academic, government, and commercial entities are involved, including FNMOC and NRL, with forecasts generated at the Navy DOD

Supercomputing Resource Center. The maximum forecast range of the data is 168 hours, produced in six-hour intervals. The update frequency is every 12 hours.

E. NAVY ESPC

The establishment of Navy ESPC by NRL has enhanced oceanic extended-range forecasting. ESPC ensemble mean forecasts are more accurate than the legacy 180-hour capability in NAVGEM alone (Barton et al. 2021). A key result of Barton et al.’s study was that ESPC outperformed climatology out to 60 days in the tropics and mid latitudes and about 45 days in Arctic and Antarctic regions. As previously discussed, only ESPC wave data was acquired for this experiment due to resource constraints. Like WWIII, our ESPC data is deterministic. The forecast update frequency is one week but forecast intervals are for three hours. The maximum forecast range for ESPC data in this experiment extends to 396 hours, more than double the range of the previously discussed systems. Refer to Table 2 for comparison of the forecasting systems used. Note that this table reflects the nature of the METOC data used in this experiment and may not be reflective of the updating frequencies in operational forecasting organizations. That is, FNMOC may be able to update ESPC faster than one week at a time. However, one week is the update frequency of the data used in our simulation.

Table 2. METOC Forecasting Systems Characteristics

	NAVGEM	WWIII	HYCOM	ESPC
Maximum Forecast Range	180 Hours	180 Hours	168 Hours	396 Hours
Forecast Update Frequency	12 Hours	12 Hours	12 Hours	1 Week
Forecast Intervals	6 Hours	6 Hours	6 Hours	3 Hours

F. TMPLAR BEHAVIOR WITH LONGER ROUTES

It is important to note that some routes will require more time to travel than the forecasting ranges. For example, some routes may require more than 180 hours of transit time, which is the maximum range for our WWIII forecasts. In this scenario, TMPLAR

will route using the maximum forecast range of WWIII, then default to climatology data for the remaining portion of the voyage. However, this is amended if we conduct replanning in route. That is, we pull updated METOC information and adjust the route accordingly with new weather information while underway. The route is planned using 180 hours of WWIII forecasts with environmental conditions for the remainder of the route represented with climatology. Then, beginning from the waypoint 180 hours into the route, a new (replanned) route between this waypoint and the destination is planned using the WWIII forecasts for the following 180 hour period.

IV. DESIGN OF EXPERIMENTS

A. DESIGN OF EXPERIMENTS EXPLAINED

The National Institute of Standards and Technology (NIST) defines DOE as “A systematic, rigorous approach to engineering problem-solving that applies principles and techniques at the data collection stage to ensure the generation of valid, defensible, and supportable engineering conclusions.” In our context, it is used to understand the overall design space, help us identify how various factors interact with one another, and help prevent confounding (MacCalman 2013). Simply put, DOE are useful when we suspect that multiple factors may be influencing our output. Design matrices are used to capture the factors and their respective values per design point. Good DOE have adequate randomization to avoid bias, replication for statistical improvements with stochastic system results, and control to maximize the information produced from a limited data set (Sanchez et al. 2017).

Advancements in computational power have given us the ability to design larger experiments and run large-scale simulations in a relatively quick span of time. However, modern computing power has not yet overcome the curse of dimensionality by brute force (Sanchez et al. 2017). If we design a full factorial experiment with 100 factors and vary these factors by only 2 levels, we get 2^{100} possible design points. With the most advanced computing systems in the world today, it would still take many lifetimes to run an experiment with all design points once. This has led to the development of different space filling designs with efficient computational requirements.

B. NEARLY ORTHOGONAL LATIN HYPERCUBES AND CROSS DESIGN

Nearly Orthogonal Latin Hypercube (NOLH) DOE are an alternative method to the full factorial design discussed in the previous section. By introducing slight correlation between all terms, we can generate a space-filling design to gain insight on a complex response surface. Note that NOLHs are designed for numeric variables only. Our DOE contains both numeric and categorical variables. To achieve adequate representation of our categorical variables, each factor level is assigned to a unique integer value in a range that

reflects the total number of levels for said factor. For example, consider a categorical factor with three levels: low, medium, and high. We would assign low a value of zero, medium a value of one, and high a value of two, thus temporarily converting our categorical variables to numeric for NOLH construction. More details of this process are discussed in Chapter V, Section E.

To highlight the efficiency of these designs, consider the 2^{100} full factorial model previously discussed. No computer exists that could complete all 2^{100} runs within a lifetime. However, an NOLH with 100 factors can be produced with only 512 design points. To visually appreciate this efficiency and space filling nature, the authors provide a comparison between the full factorial designs and NOLH designs, shown in Figure 4.

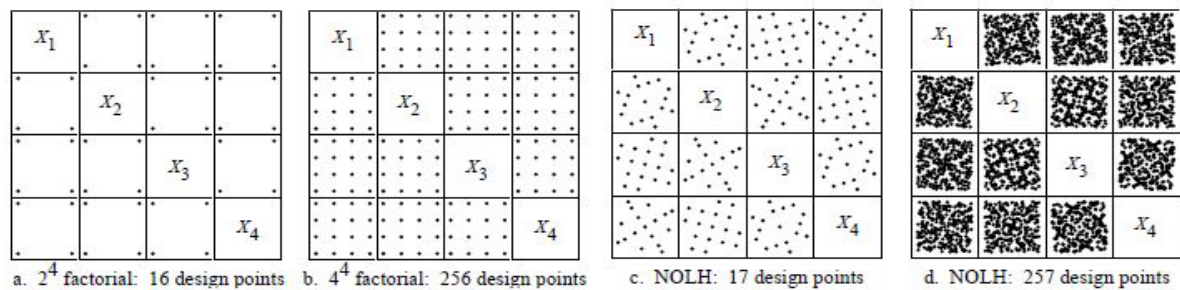


Figure 4. Scatterplot Matrices for Factorial and NOLH Designs. Source: Sanchez and Wan (2012)

Note the improvement in design space when utilizing NOLH designs over factorial designs. Also, it is important to mention that we can produce an NOLH design with 29 factors that results in 257 design points. In the factorial design in Figure 4(b), we hit 256 design points with just four factors. Sanchez and Wan (2012) explain that to improve this design space, “stacks” can be added to increase the total number of design points, a process that involves reassigning factors to different columns of the design matrix.

Lastly, it is important to mention that any design can be crossed with any other designs. For example, we can take a full factorial design and cross it with an NOLH design. This is relevant to this study, given that we cross multiple designs with a 3^2 factorial design.

V. DESIGN OF EXPERIMENTS FOR TMPLAR

A. FACTORS TO BE VARIED IN DESIGN

Our design contains both route-related factors and factors related to TMPLAR or the forecasting system. The route-related portion of the design consists of seven factors varied from the input payload parameters shown in previous chapters. These factors are “origin,” “destination,” “startDt看,” “speed,” “lateArrivalHrs,” “earlyArrivalHrs,” and “updateFreq.” The factors and information relevant to factor settings are shown in Figure 5, which is a snapshot of a comma-separated values (CSV) file prepared by the user. The first two factors (“origin” and “destination”) are categorical, and we list all potential settings. We treat the “startDt看” as a categorical factor because we have a limited amount of data available and it is not evenly spaced over time. For speed, early and late arrival hours, we provide the minimum and maximum values to be varied as integers. The “updateFreq” is a two-level categorical factor.

origin	destination	startDt看	endDt看	speed	lateArrivalHrs	earlyArrivalHrs	updateFreq
Anchorage, Alaska	Anchorage, Alaska	2020-09-27T12:01:00.000Z	To be filled.	12	0	0	"168"
Bahrain	Bahrain	2020-10-04T12:01:00.000Z		16	96	96	no_update
Busan, South Korea	Busan, South Korea	2020-10-11T12:01:00.000Z					
Cape Town, South Africa	Cape Town, South Africa	2020-10-18T12:01:00.000Z					
Diego Garcia	Diego Garcia	2020-10-27T12:01:00.000Z					
Guam	Guam	2020-11-01T12:01:00.000Z					
Manila, Philippines	Manila, Philippines	2020-11-15T12:01:00.000Z					
Mayport, Florida	Mayport, Florida	2020-11-29T12:01:00.000Z					
Naples, Italy	Naples, Italy	2020-12-06T12:01:00.000Z					
Norfolk, Virginia	Norfolk, Virginia	2020-12-13T12:01:00.000Z					
Okinawa, Japan	Okinawa, Japan	2020-12-20T12:01:00.000Z					
Trondheim, Norway	Trondheim, Norway	2020-12-27T12:01:00.000Z					
Pearl Harbor, Hawaii	Pearl Harbor, Hawaii	2021-04-04T12:01:00.000Z					
Rota, Spain	Rota, Spain	2021-04-11T12:01:00.000Z					
San Antonio, Chile	San Antonio, Chile	2021-04-18T12:01:00.000Z					
San Diego, California	San Diego, California	2021-04-25T12:01:00.000Z					
Sao Luis, Brazil	Sao Luis, Brazil	2021-08-15T12:01:00.000Z					
Singapore	Singapore	2021-08-22T12:01:00.000Z					
Souda Bay, Greece	Souda Bay, Greece	2021-09-05T12:01:00.000Z					
Sydney, Australia	Sydney, Australia	2021-09-12T12:01:00.000Z					
		2021-09-19T12:01:00.000Z					
		2021-10-03T12:01:00.000Z					
		2021-10-10T12:01:00.000Z					

Figure 5. Front End for Design Generation

Note that our “endDtg” is listed as a column in Figure 5 but is not an individual factor that is independently varied in the design. That is, our desired arrival date time group (DTG) is dependent on our departure DTG and the origin/destination pair. The calculation of our desired arrival time is discussed in Section C of this chapter.

Two other factors are of interest: the weather forecasting systems and TMPLAR objectives. These factors and levels are shown in Table 3.

Table 3. TMPLAR-Related Factors

forecast	objectives
“Legacy”	“time”
“ESPC”	“distance”
“Climate”	“fuel”

Our “forecast” and “objectives” factors, added to the seven previously discussed, give us a total of nine factors to be varied in the overall design. We discuss some of these factors in more detail in Sections B-D, provide details of the design generation process and the overall design characteristics in Section E, and describe the postprocessing system to obtain relevant output data in Section F.

B. PORT AND ROUTE SELECTION

Twenty commonly visited ports were selected throughout the globe, with emphasis on location dispersion and variability of port proximity to one another. This was done due to the findings in our literature review that suggest routes tend to be sensitive to location and length. The ports selected are in Table 4 and can be viewed in Figure 6.

Table 4. List of Port Locations

Locations	Longitude	Latitude	Locations	Longitude	Latitude
Anchorage, Alaska	150.126	61.205	Okinawa, Japan	127.639	26.233
Bahrain	50.781	26.197	Pearl Harbor, Hawaii	157.951	21.359
Busan, South Korea	129.054	35.039	Rota, Spain	-6.321	36.604
Cape Town, South Africa	18.439	33.898	San Antonio, Chile	-71.621	33.584
Diego Garcia	72.310	-7.319	San Diego, California	117.138	32.668
Guam	144.596	13.456	Sao Luis, Brazil	-44.401	-2.557
Manila, Philippines	120.931	14.583	Singapore	103.711	1.239
Mayport, Florida	-81.367	30.398	Souda Bay, Greece	24.138	35.843
Naples, Italy	14.281	40.820	Sydney, Australia	151.261	34.017
Norfolk, Virginia	-75.886	36.984	Trondheim, Norway	10.373	63.484



Figure 6. Map of Port Locations

As Figure 6 demonstrates, we have ports in every hemisphere at various latitude and longitude extremes. Each port was paired with every other port to generate possible routes for simulation. That is, there are 190 origin/destination pairs or 380 total possible routes. This ensures that routes constructed will be exposed to various METOC conditions associated with different regions of the globe. Additionally, by treating our origin and destinations as independent factors to be varied in the design, we ensure that route length will be adequately varied as well. For example, one design point may consist of Mayport, Florida and Norfolk, Virginia as an origin/destination pair. Perhaps Mayport, Florida and Sydney, Australia are in a different design point. These possibilities differ greatly in distance and regional METOC conditions.

Latitude and longitude coordinates were pulled from Google Earth Pro version 7.3.6.9345. Exact port locations were not used due to route infeasibility within TMPLAR. Specifically, coordinates too close to a land mass caused TMPLAR to conclude that no feasible sea route existed. To adjust for this, water coordinates in the immediate vicinity of port locations were used. To ensure that a feasible route existed with all 190 pairs, test routes were fed into TMPLAR before the overall simulation was conducted. More details of this process are discussed in the next section.

C. DEPARTURE AND ARRIVAL TIMES

Our departure DTGs were dependent on the availability of Navy ESPC data. The available ESPC data had forecast update frequencies of every week. The legacy systems update more often, at least once a day while some twice a day. Given this limitation, the update times of ESPC were used as our departure DTGs. This way our legacy forecasting systems would not have an advantage over ESPC before departure. For example, if we depart six days past the previous ESPC update, routes constructed with ESPC data will be using METOC information that is six days old. However, the same routes utilizing the legacy systems will have METOC information no older than one day. Navy ESPC data from 2020 and 2021 was provided by FNMOC with 23 different forecast updates. However, most of the data is for the fall of 2020 and summer of 2021. Very little data was provided for winter and spring seasons. This is a limitation in our design that should be

acknowledged. To maximize the seasonal spread with the data provided, all 23 dates were included in the design as shown in Figure 5.

To determine realistic arrival times for all origin/destination pairs, TMPLAR was run bare, without any METOC data and optimized only for time. Unrealistic start and end times were fed into the system as well, which forced TMPLAR to recompute the fastest amount of time a vessel could travel between an origin and destination pair at an average of 12 knots. Recall Figure 5, which shows the minimum average speed we vary in the overall design as 12 knots. Our minimum and maximum speeds mirrored the values in our overall design for consistency as well. A symmetric matrix was produced to capture the minimum amount of time required to travel from origin (row) to destination (column). The complete matrix is provided in Appendix A. The values in the matrix are shown in hours.

To calculate the desired arrival time for a design point, the departure date is used plus the minimum port transit time value for the specified origin/destination pair. Additionally, 96 hours is added as a buffer for “earlyArrivalHrs” feasibility. That is, we need an arrival time that is greater than the earliest possible arrival time if we want to have an early arrival window. If our desired arrival time is our earliest possible arrival time, the “earlyArrivalHrs” factor is essentially useless since there would be no window to arrive early.

D. UPDATE FREQUENCY

Our “updateFreq” factor is categorical and has two levels. The “168” value represents replanning every week or 168 hours. This update frequency matches the ESPC forecast update intervals to avoid giving our legacy systems an advantage while underway. For example, if the update frequency is set to daily, our legacy systems will have updated and current information that may cause rerouting. However, the same design point with ESPC will have no new information after one day, thus routes will not adjust. The “no_update” value ensures that no replanning takes place while the route is being executed. That is, the route will not change after it is constructed prior to departure.

E. OVERALL DESIGN CONSTRUCTION

A combination of Python version 3.8 and Ruby version 3.1.2 software was used to quickly construct our overall DOE. Desired route-related factors to vary were entered into a CSV file as previously shown in Figure 5. The column labels matched the TMPLAR input payload parameters to minimize confusion. For categorical factors, all levels were listed under their respective factor label. For numeric data, minimum values were entered above the maximum values.

The Ruby scripts used come from the data farming Ruby gem, which is a publicly available set of scripts for design generation and file manipulation available at <https://rubygems.org/gems/datafarming> (Sanchez 2021). Note that we rely on the “stacks_nolhs.rb” function to generate our NOLH. The minimum NOLH sizes are 17 design points for up to 7 factors, 33 design points for 8–11 factors, 65 design points for 12–16 factors, 129 design points for 17–22 factors, 257 design points for 23–29 factors, or 512 design points for 30–100 factors.

1. Modification of Categorical Variables and NOLH Construction

A Python script was written to identify categorical and numeric factors from the front-end CSV. As shown in Figure 5, we have four categorical variables that need to be converted to integer values prior to NOLH construction. Origin/destination ports were assigned a value between 0–19, our departure dates were assigned a value between 0–22, and our update frequencies were assigned to either zero or one. These assignments were stored in a dictionary for post NOLH construction translation. Once all factors reflected a numeric type, the information was converted into a feasible text file for Ruby digestion. The same Python script prompts for the desired number of stacks, feeds the input file into Ruby via the command line, and with the “stacks_nolhs.rb” function, an NOLH is produced as a text file. Since all eight columns are passed into the “stacks_nolhs.rb” function from Figure 5, we will produce an NOLH with 33 design points with a single stack unless we select a larger number of levels with the “-l” option. However, we chose to use the “-s 7” option for “stack_nolhs.rb” to create seven stacks to achieve a total of 225 design points in the overall NOLH design. This stacked NOLH has better space-filling properties for the

quantitative factors, and a greater number of combinations of the categorical factors. The NOLH is converted back into a Pandas DataFrame in Python for further manipulation. All categorical factors are then translated from their respective integer assignments back into their original values. Note that orthogonality between all parameters will no longer apply, but adequate representation of our categorical factors is achieved. A snapshot of this design is shown in Figure 7.

origin	destination	startDtg	endDtg	speed	lateArrivalHrs	earlyArrivalHrs	updateFreq
Sydney, Australia	Busan, South Korea	2020-12-20T12:01:00.000Z	To be filled.	16	60	66	"168"
Singapore	Sydney, Australia	2020-10-18T12:01:00.000Z	To be filled.	14	18	72	"168"
Singapore	Naples, Italy	2021-09-19T12:01:00.000Z	To be filled.	12	57	69	"168"
Trondheim, Norway	Singapore	2021-10-10T12:01:00.000Z	To be filled.	16	15	78	"168"
Souda Bay, Greece	Bahrain	2020-12-20T12:01:00.000Z	To be filled.	15	69	39	no_update
Souda Bay, Greece	Souda Bay, Greece	2020-11-29T12:01:00.000Z	To be filled.	14	21	15	no_update
Rota, Spain	Norfolk, Virginia	2021-10-03T12:01:00.000Z	To be filled.	12	63	36	no_update
Okinawa, Japan	Rota, Spain	2021-10-03T12:01:00.000Z	To be filled.	16	24	21	no_update
Pearl Harbor, Hawaii	Guam	2020-11-01T12:01:00.000Z	To be filled.	15	30	0	"168"
San Antonio, Chile	Pearl Harbor, Hawaii	2020-11-15T12:01:00.000Z	To be filled.	13	51	9	"168"
San Antonio, Chile	Diego Garcia	2021-08-22T12:01:00.000Z	To be filled.	13	6	12	"168"
San Diego, California	San Antonio, Chile	2021-04-18T12:01:00.000Z	To be filled.	15	93	45	"168"
Trondheim, Norway	Cape Town, South Africa	2020-10-27T12:01:00.000Z	To be filled.	14	12	93	no_update
Sao Luis, Brazil	Trondheim, Norway	2020-12-06T12:01:00.000Z	To be filled.	13	54	90	no_update
Pearl Harbor, Hawaii	Diego Garcia	2021-09-12T12:01:00.000Z	To be filled.	14	0	63	no_update
San Diego, California	Pearl Harbor, Hawaii	2021-04-11T12:01:00.000Z	To be filled.	15	87	54	no_update
Okinawa, Japan	Okinawa, Japan	2020-12-27T12:01:00.000Z	To be filled.	14	48	48	no_update
Anchorage, Alaska	Singapore	2021-04-04T12:01:00.000Z	To be filled.	13	36	30	no_update
Busan, South Korea	Anchorage, Alaska	2021-09-12T12:01:00.000Z	To be filled.	14	78	24	no_update

Figure 7. Snapshot of the First 19 Rows of Design Prior to Cleaning and Crossing

For future and potentially larger experiments, the user may also wish to specify both the basic design size with the “-l” option and the number of stacks with the “-s” option to determine how many levels of categorical and integer-valued factors appear. For example, suppose there were 40 “startDtg” levels in the front-end file instead of our 23. Both “stack_nolhs.rb -l 33 -s 6” and “stack_nolhs.rb -l 65 -s 3” produce designs with 193 design points. The first would use only 33 of the 40 “startDtg” levels, the second would use all 40 start dates and repeat some of them more than once.

2. Cleaning and Crossing

Additional preparation is required before we can cross our design with our remaining two factors. First, our “endDtg” values need to be filled in. This is done by

calling the minimum port transit time matrix discussed in Section C of this chapter, finding the values for each origin/destination pair, and adding our buffer time to allow for reasonable “earlyArrivalHrs.” These actions are accomplished within the same Python script. Also, design points with the same origin and destination values need to be identified and dropped. Five design points had this issue and were consequently removed. This reduced the design to 220 design points prior to crossing and a snapshot can be viewed in Figure 8.

origin	destination	startDtg	endDtg	speed	lateArrivalHrs	earlyArrivalHrs	updateFreq
Sydney, Australia	Busan, South Korea	2020-12-20T12:01:00.000Z	2021-01-01T21:31:00.000Z	16	60	66	"168"
Singapore	Sydney, Australia	2020-10-18T12:01:00.000Z	2020-11-01T04:01:00.000Z	14	18	72	"168"
Singapore	Naples, Italy	2021-09-19T12:01:00.000Z	2021-10-12T10:37:00.000Z	12	57	69	"168"
Trondheim, Norway	Singapore	2021-10-10T12:01:00.000Z	2021-11-02T17:43:00.000Z	16	15	78	"168"
Souda Bay, Greece	Bahrain	2020-12-20T12:01:00.000Z	2021-01-13T23:01:00.000Z	15	69	39	no_update
Rota, Spain	Norfolk, Virginia	2021-10-03T12:01:00.000Z	2021-10-12T05:37:00.000Z	12	63	36	no_update
Okinawa, Japan	Rota, Spain	2021-10-03T12:01:00.000Z	2021-11-02T16:01:00.000Z	16	24	21	no_update
Pearl Harbor, Hawaii	Guam	2020-11-01T12:01:00.000Z	2020-11-10T18:43:00.000Z	15	30	0	"168"
San Antonio, Chile	Pearl Harbor, Hawaii	2020-11-15T12:01:00.000Z	2020-11-27T18:55:00.000Z	13	51	9	"168"
San Antonio, Chile	Diego Garcia	2021-08-22T12:01:00.000Z	2021-09-10T12:19:00.000Z	13	6	12	"168"
San Diego, California	San Antonio, Chile	2021-04-18T12:01:00.000Z	2021-04-29T16:43:00.000Z	15	93	45	"168"
Trondheim, Norway	Cape Town, South Africa	2020-10-27T12:01:00.000Z	2020-11-11T03:25:00.000Z	14	12	93	no_update
Sao Luis, Brazil	Trondheim, Norway	2020-12-06T12:01:00.000Z	2020-12-17T04:49:00.000Z	13	54	90	no_update
Pearl Harbor, Hawaii	Diego Garcia	2021-09-12T12:01:00.000Z	2021-10-01T14:37:00.000Z	14	0	63	no_update
San Diego, California	Pearl Harbor, Hawaii	2021-04-11T12:01:00.000Z	2021-04-18T18:37:00.000Z	15	87	54	no_update
Anchorage, Alaska	Singapore	2021-04-04T12:01:00.000Z	2021-04-19T01:07:00.000Z	13	36	30	no_update
Busan, South Korea	Anchorage, Alaska	2021-09-12T12:01:00.000Z	2021-09-23T03:13:00.000Z	14	78	24	no_update
Busan, South Korea	Trondheim, Norway	2020-10-11T12:01:00.000Z	2020-10-25T16:13:00.000Z	16	39	27	no_update
Naples, Italy	Busan, South Korea	2020-09-27T12:01:00.000Z	2020-10-29T12:13:00.000Z	12	81	18	no_update

Figure 8. Snapshot of First 19 Rows Prior to Crossing

Once desired arrival times were entered and the five design points were removed, we need to incorporate the remaining factors into the design. Crossing the forecasting system and objective factors would yield $3^2=9$ design points and a final, crossed design with $220 \times 9=1980$ total design points. Our completed design was exported to a CSV file for further data manipulation. A snapshot of the final design is shown in Figure 9. Note that if we were to design a full factorial experiment with corresponding numbers of levels for each factor, we would have $2^1 3^2 5^1 23^1 33^2 380^1$, or 856,607,400 total design points. This demonstrates the efficiency of our final design. The maximum pairwise correlation among any pair of quantitative factors is 0.0164.

origin	destination	startDtg	endDtg	speed	lateArrivalHrs	earlyArrivalHrs	updateFreq	forecast	objectives
Sydney, Australia	Busan, South Korea	2020-12-20T12:01:00.000Z	2021-01-01T21:31:00.000Z	16	60	66	"168"	Legacy	time
Singapore	Sydney, Australia	2020-10-18T12:01:00.000Z	2020-11-01T04:01:00.000Z	14	18	72	"168"	Legacy	time
Singapore	Naples, Italy	2021-09-19T12:01:00.000Z	2021-10-12T10:37:00.000Z	12	57	69	"168"	Legacy	time
Trondheim, Norway	Singapore	2021-10-10T12:01:00.000Z	2021-11-02T17:43:00.000Z	16	15	78	"168"	Legacy	time
Souda Bay, Greece	Bahrain	2020-12-20T12:01:00.000Z	2021-01-13T23:01:00.000Z	15	69	39	no_update	Legacy	time
Rota, Spain	Norfolk, Virginia	2021-10-03T12:01:00.000Z	2021-10-12T05:37:00.000Z	12	63	36	no_update	Legacy	time
Okinawa, Japan	Rota, Spain	2021-10-03T12:01:00.000Z	2021-11-02T16:01:00.000Z	16	24	21	no_update	Legacy	time
Pearl Harbor, Hawaii	Guam	2020-11-01T12:01:00.000Z	2020-11-10T18:43:00.000Z	15	30	0	"168"	Legacy	time
San Antonio, Chile	Pearl Harbor, Hawaii	2020-11-15T12:01:00.000Z	2020-11-27T18:55:00.000Z	13	51	9	"168"	Legacy	time
San Antonio, Chile	Diego Garcia	2021-08-22T12:01:00.000Z	2021-09-10T12:19:00.000Z	13	6	12	"168"	Legacy	time
San Diego, California	San Antonio, Chile	2021-04-18T12:01:00.000Z	2021-04-29T16:43:00.000Z	15	93	45	"168"	Legacy	time
Trondheim, Norway	Cape Town, South Africa	2020-10-27T12:01:00.000Z	2020-11-11T03:25:00.000Z	14	12	93	no_update	Legacy	time
Sao Luis, Brazil	Trondheim, Norway	2020-12-06T12:01:00.000Z	2020-12-17T04:49:00.000Z	13	54	90	no_update	Legacy	time
Pearl Harbor, Hawaii	Diego Garcia	2021-09-12T12:01:00.000Z	2021-10-01T14:37:00.000Z	14	0	63	no_update	Legacy	time
San Diego, California	Pearl Harbor, Hawaii	2021-04-11T12:01:00.000Z	2021-04-18T18:37:00.000Z	15	87	54	no_update	Legacy	time
Anchorage, Alaska	Singapore	2021-04-04T12:01:00.000Z	2021-04-19T01:07:00.000Z	13	36	30	no_update	Legacy	time
Busan, South Korea	Anchorage, Alaska	2021-09-12T12:01:00.000Z	2021-09-23T03:13:00.000Z	14	78	24	no_update	Legacy	time
Busan, South Korea	Trondheim, Norway	2020-10-11T12:01:00.000Z	2020-10-25T16:13:00.000Z	16	39	27	no_update	Legacy	time
Naples, Italy	Busan, South Korea	2020-09-27T12:01:00.000Z	2020-10-29T12:13:00.000Z	12	81	18	no_update	Legacy	time

Figure 9. Snapshot of First 19 Rows in Overall Design

3. Preparation for TMPLAR Digestion

Further action was still required to convert the completed design from CSV to JSON for TMPLAR digestion. An additional Python script was written to accomplish this. Given the relatively small number of design points, computation time was not stressed in code development. Users should be aware that this script may require longer computational times with larger designs. The CSV design was converted into a Pandas DataFrame for easy manipulation. Two main loops were used to iterate through each design point and each column. For every design point, a new input payload was prepared and stored as a dictionary to be exported. Column names in the design were matched with payload dictionary keys and relevant information from the design points were entered as payload dictionary values. At the completion of each design point iteration, the finalized JSON payload was exported into a separate folder for TMPLAR digestion. A total of 1980 payloads, one for each design point, were produced and fed into TMPLAR for analysis.

F. TMPLAR ROUTE CONSTRUCTION AND ANALYSIS PROCESS

The route construction and analysis process using TMPLAR involves two steps. First, TMPLAR ingests our input payloads and constructs a route recommendation based on our parameter selections. Relevant output information is provided based on the METOC data selected in the input payload. Specifically, the calculations are based on forecasting data. The second step involves running these routes through TMPLAR again but subjecting

them to a “ground truth.” That is, we send the ships along the same path, but recalculate output values based on the actual weather conditions that took place during that time. The METOC information used for our “ground truth” is based on ERA5 reanalysis data that is reflected in three hours intervals. ERA5 is the fifth generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis for climate and weather and can provide estimates for atmospheric, ocean-wave, and land-surface conditions (Copernicus Climate Change Service, Climate Data Store 2023). It is necessary to mention that we do not compare TMPLAR’s estimated outputs with forecast data against the values calculated with “ground truth” METOC information. However, this would be an interesting area for future research.

VI. ANALYSIS AND RESULTS

We approach our analysis in this chapter by addressing multiple topics to provide information about simulation output issues, analysis on fuel versus time and distance objectives, address findings related to our research question, and cover the improvements in TMPLAR robustness because of large-scale simulation. Python version 3.8 was used to extract relevant route information for each JSON output and organize it with our design matrix in a CSV file for analysis. Analysis was conducted and graphs were built using JMP Pro version 16 software. Route visualizations were built using Keyhole Markup Language (KML) files in Google Earth Pro version 7.3.6.9345.

Our goal is to assess the performance of TMPLAR routes using ESPC against legacy and climatology METOC systems. We focus on three main outcome metrics: fuel consumption, calculated in thousands of gallons; time, measured in hours; and maximum wave height endured along route, in feet. The goal of route planning, as implemented in TMPLAR, is to minimize the amount of fuel expended on a route, minimize the amount of time it takes to travel, or minimize exposure to rough sea states.

Recall that our design was crossed with each forecasting system, thus every route will have output for ESPC, legacy, and climatology data (if TMPLAR successfully runs for those design points). When we reference ESPC versus legacy or ESPC versus climatology, we are comparing the differences in output. For example, consider design points 0 and 660, whose inputs are identical except for the METOC system used. In an ESPC versus legacy scenario comparing fuel, we subtract the fuel consumption of our legacy design point from the fuel consumption of our ESPC design point. A negative value indicates that the route built with ESPC data used less fuel. A positive value indicates that the ESPC route used more fuel. Zero values indicate a “tie,” generally due to identical route construction. The difference equations are shown below for ESPC versus legacy and ESPC versus climatology respectively.

$$ESPC_i - Legacy_i, i \in I = \{fuel, time\} \quad (1)$$

$$ESPC_i - Climate_i, i \in I = \{fuel, time\} \quad (2)$$

Additional insight is provided through relative differences with respect to climatology results. The relative difference equations are shown below.

$$\frac{ESPC_i - Legacy_i}{Climate_i}, i \in I = \{fuel, time\} \quad (3)$$

$$\frac{ESPC_i - Climate_i}{Climate_i}, i \in I = \{fuel, time\} \quad (4)$$

We use these equations to produce general summary statistics and visualizations. Note that max wave height is not analyzed in a relative manner in this report.

A. ORIGINAL DESIGN OUTPUT AND ADDITIONAL DESIGNS

Of the original 1980 payloads inputted into TMPLAR, 1672 successfully ran and generated feasible routes for analysis. All 1320 routes optimized for time and distance were successful. Only 352 out of the 660 routes optimized for fuel successfully ran, or approximately 53%. Although this issue has not been fully resolved due to the time constraints of this study, we believe the error is caused by port locations being too close to land. We noticed the same issue in our earlier simulation runs and had to adjust port locations further offshore. More routes would run the further from shore we located our ports.

Given the limited number of successful simulation runs, our original design was used to gain insight into overall TMPLAR performance relative to objective selection. That is, we compare the outputs of routes optimized by time, distance, and fuel. Our analysis appears in Section B.

As a consequence of the fuel optimization routing issues, an additional DOE was built that focuses solely on our fuel objective. That is, all design points in our new design were optimized for fuel minimization. A subset of 15 origin/destination pairs that successfully produced routes were crossed with a new design. More details and analysis of our new design are discussed in Section C of this chapter, where we analyze ESPC

performance against the legacy and climatology systems while explicitly optimizing for fuel.

B. FUEL VERSUS TIME AND DISTANCE OBJECTIVES

As discussed in previous chapters, our overall design consists of 220 design points crossed nine times for a total of 1980 input payloads. Simply put, we have 220 possible routes that are optimized in TMPLAR with respect to our three objectives using our three forecast systems. The origin/destination information for each route and their desired departure and arrival times are available in Appendix B. Recall that only 53% of our payloads optimizing for fuel ran successfully. Consequently, we only have complete information for all objectives and forecasting systems for 117 out of the 220 routes.

1. Regional, Seasonal, and Location Variation

To classify these routes for regional analysis, each route was broken down into one of four quadrants globally: NE, NW, SE, and SW. Note that these classifications are based on our results and were not inputs themselves in the overall design. This determination was based on the region containing the largest number of waypoints for each route produced. Regional classification was identical for each design point that successfully ran, regardless of objective or forecast system. Most routes fell under the quadrants in the northern hemisphere.

Routes were also broken down by season, based on our desired departure and arrival DTGs, based on which season most of the days in the transit window fell under. Given that these times are dependent on the availability of ESPC data, most routes are in the fall. Table 5 is provided to illustrate the regional counts by season in our initial design.

Table 5. Regional Counts by Season

	Fall	Winter	Spring	Summer	Total
NE	22	5	11	7	45
NW	20	0	4	6	30
SE	16	1	9	2	28
SW	8	2	1	3	14
Total	66	8	25	18	117

To gain insight into the variation in route length, it is useful to visualize the minimum transit times required between our 117 origin/destination pairs. Recall that our minimum transit times are based on TMPLAR routes with time as the objective and no METOC considerations. Design points with lower transit time values indicate that the origin/destination ports are closer to one another, while larger values indicate that the ports are more distant. The distribution can be seen in the histogram in Figure 10.

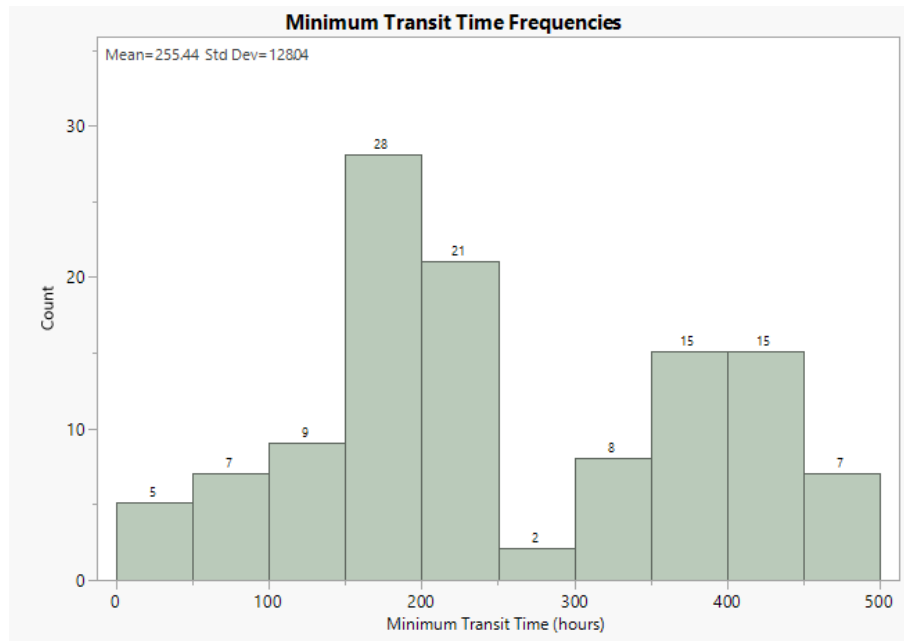


Figure 10. Minimum Transit Times in Original Design

We see good variation in the locations of origins and destinations in our design. We have a minimum value of 21.3 hours, the route from Okinawa Japan to Busan, South Korea and a maximum value of 491 hours, the route from Bahrain to Souda Bay, Greece (without using the Suez Canal).

2. Time, Distance, and Fuel Objectives

For each design point, TMPLAR produced identical routes using the time and distance objectives. This is of no surprise, given that TMPLAR constructs routes via the great circle distance when time or distance is selected for optimization. As a result, there

is no variability of output to compare forecasting systems when time or distance is selected for optimization. Thus, we primarily rely on routes optimized for fuel to gain insight into forecasting system performance in Section C. However, there is still value in comparing our time and distance routes against our fuel routes for operational insight. We approach this analysis using differences and relative differences between our ESPC routes optimized for fuel and ESPC routes optimized for time. The difference and relative difference equations are shown below, respectively.

$$Fuel\ Obj_i - Time\ Obj_i, i \in I = \{fuel, time\} \quad (5)$$

$$\frac{Fuel\ Obj_i - Time\ Obj_i}{Time\ Obj_i}, i \in I = \{fuel, time\} \quad (6)$$

Note that since the outputs from routes optimized for time or distance are identical, either set of routes can be used when comparing outputs from routes optimized for fuel. In our case, we use routes optimized for time.

The summary statistics for the differences and relative differences of our fuel outputs are shown in Figure 11.

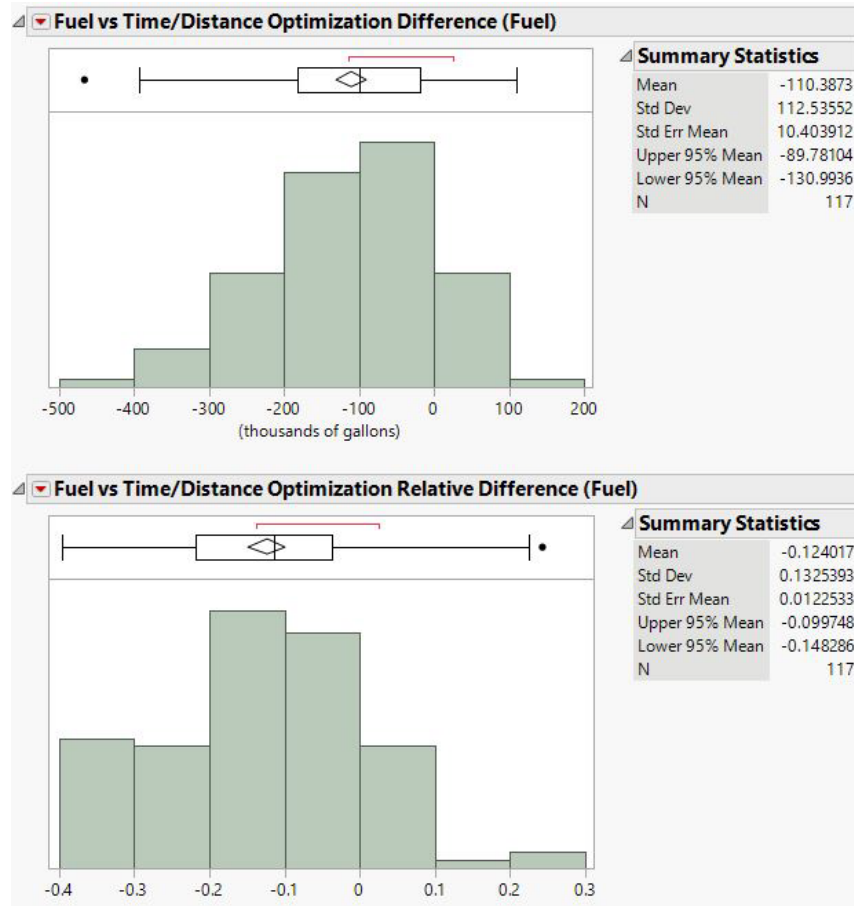


Figure 11. Fuel vs. Time/Distance Optimization Summary Statistics: Negative Values Indicate Fuel Savings When Optimizing for Fuel

Based on the data in Figure 11, we see strong evidence that the fuel minimization objective improves the overall fuel consumption for each route. We see an average fuel savings of 110,000 gallons in our difference distribution and an average savings of around 12 percent in our relative difference distribution.

The summary statistics for the differences and relative differences of our time outputs are shown in Figure 12.

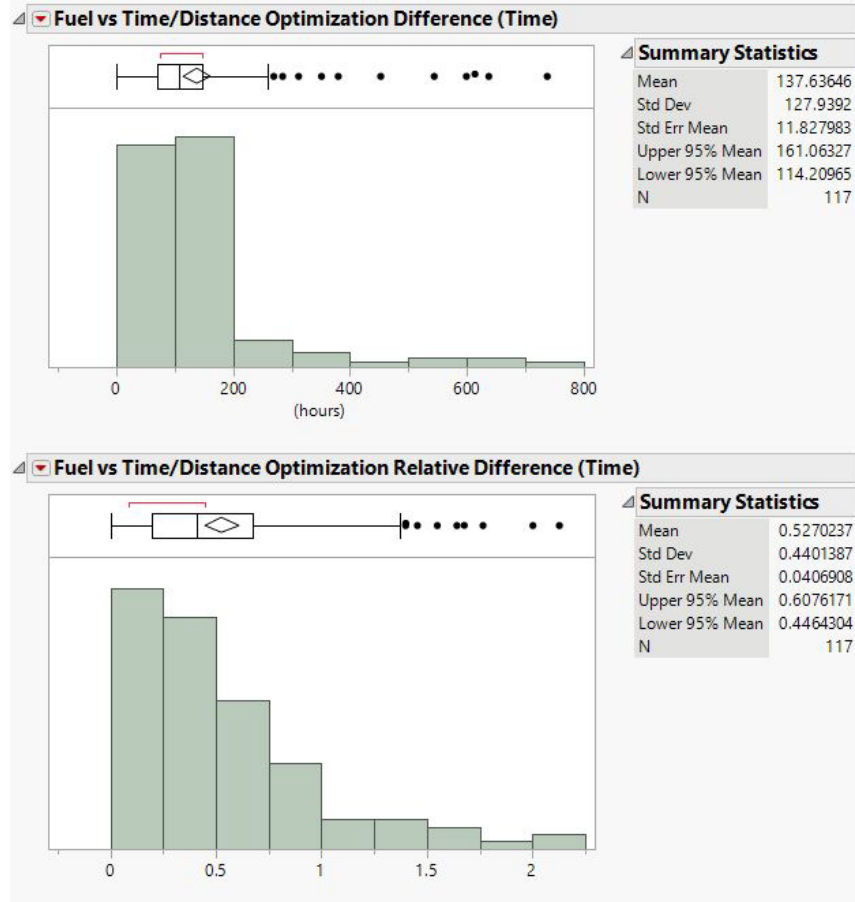


Figure 12. Fuel vs. Time/Distance Optimization Summary Statistics: Positive Values Indicate Longer Transit Times When Optimizing for Fuel

The summary statistics provided in Figure 12 show that, on average, our routes optimized for fuel take around 138 hours longer than when we optimize based on time or distance. Our relative difference statistics suggest that, on average, optimizing for fuel requires 53 percent more transit time. Further analysis reveals that not a single route that was optimized for fuel arrived within the allowable window—the desired arrival DTG plus the number of hours permitted to be late. To ensure that this was not an ESPC specific issue, our late arrival hours were calculated for our legacy and climatology routes as well. The summary statistics for our late arrivals are provided in Figure 13.

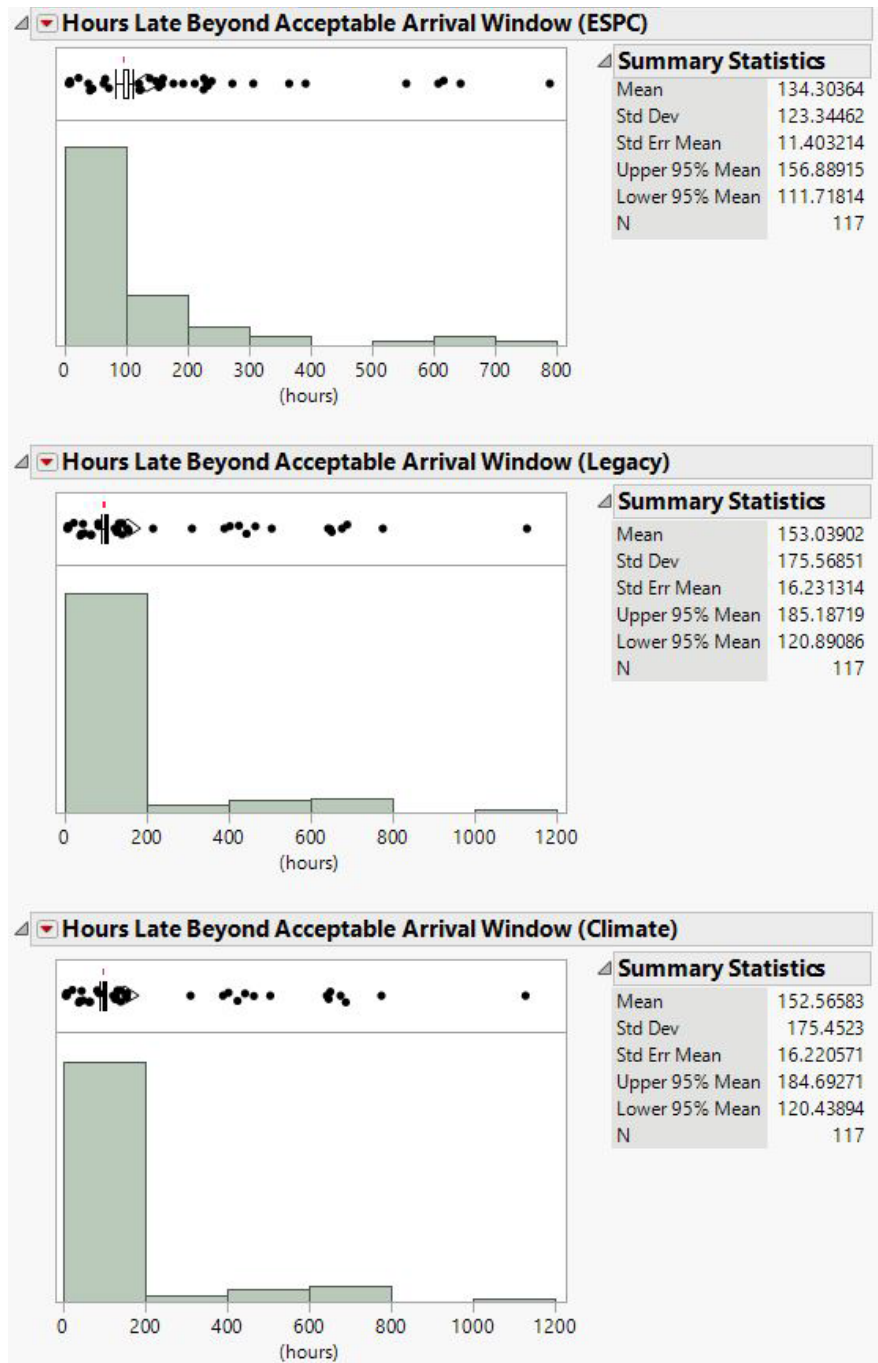


Figure 13. Late Arrival Times: Hours Beyond the Acceptable Arrival Window Specified in Payload

Our arrival times, when optimizing for fuel consumption, are over five to six days late on average. We see this pattern regardless of the forecasting system used. However, our ESPC routes tend to be the “least late” on average when optimizing for fuel. Based on the

information provided in Figures 11 and 12, we see that there is a clear tradeoff between optimizing for time or distance versus optimizing for fuel. Routing to minimize fuel consumption comes at a great cost in terms of transit duration.

With respect to the maximum wave heights encountered for both objectives, one objective does not appear to outperform the other. Figure 14 compares the distributions of the maximum wave heights experienced for our routes optimized for time/distance and fuel. Green points represent fuel routes that outperform time/distance routes and red points represent time/distance routes that outperform fuel routes.

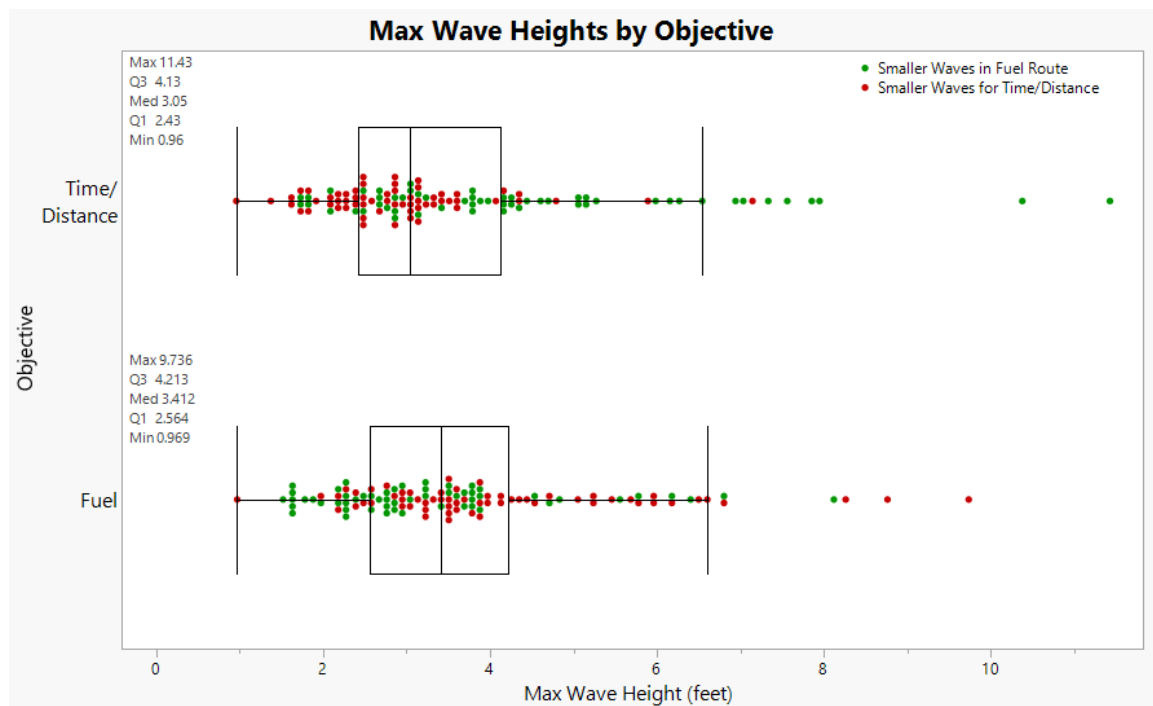


Figure 14. Fuel vs. Time/Distance Optimization Max Wave Height Performance

Our outliers indicate that when one set of routes experiences extreme wave heights, the same route minimized for the alternative objective tends to perform better. This is evident with our green outliers under time/distance and red outliers under fuel.

C. FORECASTING SYSTEMS FOR OPTIMIZING FUEL OBJECTIVE

As discussed in the first section of this chapter, 15 routes that successfully ran in the first design were crossed with a new design. Three routes were deliberately chosen for each 100-hour minimum transit time interval up to 500 hours to maintain port location variability. Additional crossing was done with each forecasting system, but not the other objectives. That is, all design points have an objective of minimizing fuel consumption. The 15 routes can be seen in Table 6.

Table 6. Routes in New Design

Origin	Destination	Minimum Transit Time (hours)	Primary Region (Climate)
San Diego, California	Bahrain	482.6	NE*
Bahrain	Norfolk, Virginia	445.3	SE
Okinawa, Japan	Bahrain	442.3	NE
Diego Garcia	Mayport, Florida	382.7	SW*
Busan, South Korea	San Antonio, Chile	356.6	NW*
San Diego, California	Singapore	320.3	NE
Trondheim, Norway	Cape Town, South Africa	255.4	NW
Singapore	Sydney, Australia	232	SE
Okinawa, Japan	San Diego, California	205	NW
Sao Luis, Brazil	Souda Bay, Greece	184.9	NW
Mayport, Florida	Naples, Italy	171	NW
Cape Town, South Africa	Diego Garcia	167.8	SE
Anchorage, Alaska	Pearl Harbor, Hawaii	89.3	NW
Rota, Spain	Souda Bay, Greece	55.4	NE
Manila, Philippines	Okinawa, Japan	48.5	NE

* Primary Region is Different for Some Routes Produced with ESPC or Legacy

Note that the origins and destinations were not independently varied in this new design like the original. Most of the regional labels for each origin/destination pair are the same by forecasting system used, but a few are different. We analyze these differences later in this section.

Each of these routes is subject to the conditions set in the new design. A snapshot of our new design is shown in Figure 15. Note that we construct this design using the same techniques from the original design. That is, we modify our categorical variables to build an NOLH to achieve adequate representation of our non-numeric factors.

startDtg	endDtg	speed	lateArrivalHrs	earlyArrivalHrs	updateFreq
2020-11-29T12:01:00.000Z	To be filled.	15	36	24	no_update
2020-10-04T12:01:00.000Z	To be filled.	16	54	0	"168"
2020-10-18T12:01:00.000Z	To be filled.	12	24	60	no_update
2020-10-27T12:01:00.000Z	To be filled.	13	96	54	"168"
2021-08-22T12:01:00.000Z	To be filled.	14	12	30	"168"
2021-10-10T12:01:00.000Z	To be filled.	14	78	6	no_update
2021-04-18T12:01:00.000Z	To be filled.	16	30	84	"168"
2021-04-04T12:01:00.000Z	To be filled.	15	90	78	no_update
2020-12-27T12:01:00.000Z	To be filled.	14	48	48	no_update
2021-04-25T12:01:00.000Z	To be filled.	13	60	72	"168"
2021-10-03T12:01:00.000Z	To be filled.	13	42	96	no_update
2021-09-12T12:01:00.000Z	To be filled.	16	72	36	"168"
2021-09-05T12:01:00.000Z	To be filled.	15	0	42	no_update
2020-11-15T12:01:00.000Z	To be filled.	14	84	66	no_update
2020-09-27T12:01:00.000Z	To be filled.	15	18	90	"168"
2020-12-06T12:01:00.000Z	To be filled.	12	66	12	no_update
2020-12-20T12:01:00.000Z	To be filled.	13	6	18	"168"
2021-10-10T12:01:00.000Z	To be filled.	14	24	90	no_update
2020-11-15T12:01:00.000Z	To be filled.	14	0	30	no_update

Figure 15. Snapshot of First 19 Rows in New Design Before Crossing

As Figure 15 shows, the design before any additional crossings only varies five factors. Using five stacks with a 17-design point NOLH, we get a total of 81 design points and a maximum pairwise correlation among any two quantitative factors of 0.0188. Each of the 15 routes was crossed with the design, resulting in 1215 design points. Further crossing was done with our three forecasting systems, giving our completed design 3645 total design points. A snapshot is shown in Figure 16. Input payloads were then generated for each design point and inputted into TMPLAR for route construction.

origin	destination	startDtg	endDtg	speed	lateArrivalHrs	earlyArrivalHrs	updateFreq	forecast	objectives
San Diego, California	Bahrain	2020-11-29T12:01:00.000Z	2020-12-23T14:37:00.000Z	15	36	24	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-10-04T12:01:00.000Z	2020-10-28T14:37:00.000Z	16	54	0	"168"	ESPC	fuel
San Diego, California	Bahrain	2020-10-18T12:01:00.000Z	2020-11-11T14:37:00.000Z	12	24	60	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-10-27T12:01:00.000Z	2020-11-20T14:37:00.000Z	13	96	54	"168"	ESPC	fuel
San Diego, California	Bahrain	2021-08-22T12:01:00.000Z	2021-09-15T14:37:00.000Z	14	12	30	"168"	ESPC	fuel
San Diego, California	Bahrain	2021-10-10T12:01:00.000Z	2021-11-03T14:37:00.000Z	14	78	6	no_update	ESPC	fuel
San Diego, California	Bahrain	2021-04-18T12:01:00.000Z	2021-05-12T14:37:00.000Z	16	30	84	"168"	ESPC	fuel
San Diego, California	Bahrain	2021-04-04T12:01:00.000Z	2021-04-28T14:37:00.000Z	15	90	78	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-12-27T12:01:00.000Z	2021-01-20T14:37:00.000Z	14	48	48	no_update	ESPC	fuel
San Diego, California	Bahrain	2021-04-25T12:01:00.000Z	2021-05-19T14:37:00.000Z	13	60	72	"168"	ESPC	fuel
San Diego, California	Bahrain	2021-10-03T12:01:00.000Z	2021-10-27T14:37:00.000Z	13	42	96	no_update	ESPC	fuel
San Diego, California	Bahrain	2021-09-12T12:01:00.000Z	2021-10-06T14:37:00.000Z	16	72	36	"168"	ESPC	fuel
San Diego, California	Bahrain	2021-09-05T12:01:00.000Z	2021-09-29T14:37:00.000Z	15	0	42	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-11-15T12:01:00.000Z	2020-12-09T14:37:00.000Z	14	84	66	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-09-27T12:01:00.000Z	2020-10-21T14:37:00.000Z	15	18	90	"168"	ESPC	fuel
San Diego, California	Bahrain	2020-12-06T12:01:00.000Z	2020-12-30T14:37:00.000Z	12	66	12	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-12-20T12:01:00.000Z	2021-01-13T14:37:00.000Z	13	6	18	"168"	ESPC	fuel
San Diego, California	Bahrain	2021-10-10T12:01:00.000Z	2021-11-03T14:37:00.000Z	14	24	90	no_update	ESPC	fuel
San Diego, California	Bahrain	2020-11-15T12:01:00.000Z	2020-12-09T14:37:00.000Z	14	0	30	no_update	ESPC	fuel

Figure 16. Snapshot of First 19 Rows in Completed New Design

Of the 3645 input payloads ingested by TMPLAR, 3640 successfully constructed routes, or over 99%. As a result, we have significantly more design points for fuel analysis than our original design.

To analyze the performance of routes produced with our three forecasting systems, fuel consumption, transit time, and maximum wave height outputs were compared. Unlike the analysis conducted on our original design, differences and relative differences of outputs are studied to compare ESPC with our legacy and climatology systems. Again, negative values signal cost savings with ESPC and positive values signal additional costs in our output metrics.

1. Exploratory Data Analysis for New Design

Like the original design, our routes are predominantly through the northern hemisphere. We also see a similar spread in seasonal variation. This is consistent with our ESPC availability as well. Table 7 illustrates the regional counts (for climatology routes) by season.

Table 7. Regional Counts by Season in New Design

	Fall	Winter	Spring	Summer	Total
NE	235	30	75	65	405
NW	270	36	90	90	486
SE	142	18	45	41	246
SW	48	6	15	9	78
Total	695	90	225	205	1215

Analysis of the differences in regional classification of routes was also useful. Our San Diego, CA to Bahrain route, had 18 design points with routes classified as NW, while the remaining 225 were classified as NE. Nine NW routes were generated using the legacy system. The remaining nine routes were from identical design points, except they were routed with climatology. Plotting the waypoints revealed that our 18 routes went across large land masses as shown in Figure 17.



Figure 17. Outliers in New Design

Our routes shown in green are true sea routes and were classified as NE. The routes shown in red were classified as NW. As a result of this finding, all 27 design points associated with this route were discarded. That is, the nine legacy, nine climatology, and the nine ESPC routes we would have used to compare fuel usage and other outputs were removed from future analysis.

In our Diego Garcia to Mayport, FL routes, three design points were classified as SE and the remaining 240 were classified as SW. In our three SE routes, ESPC routed our ship further north after passing the southern tip of Africa. Our SE ESPC routes are shown in green while the legacy and climatology routes for the same design points are shown in red in Figure 18.

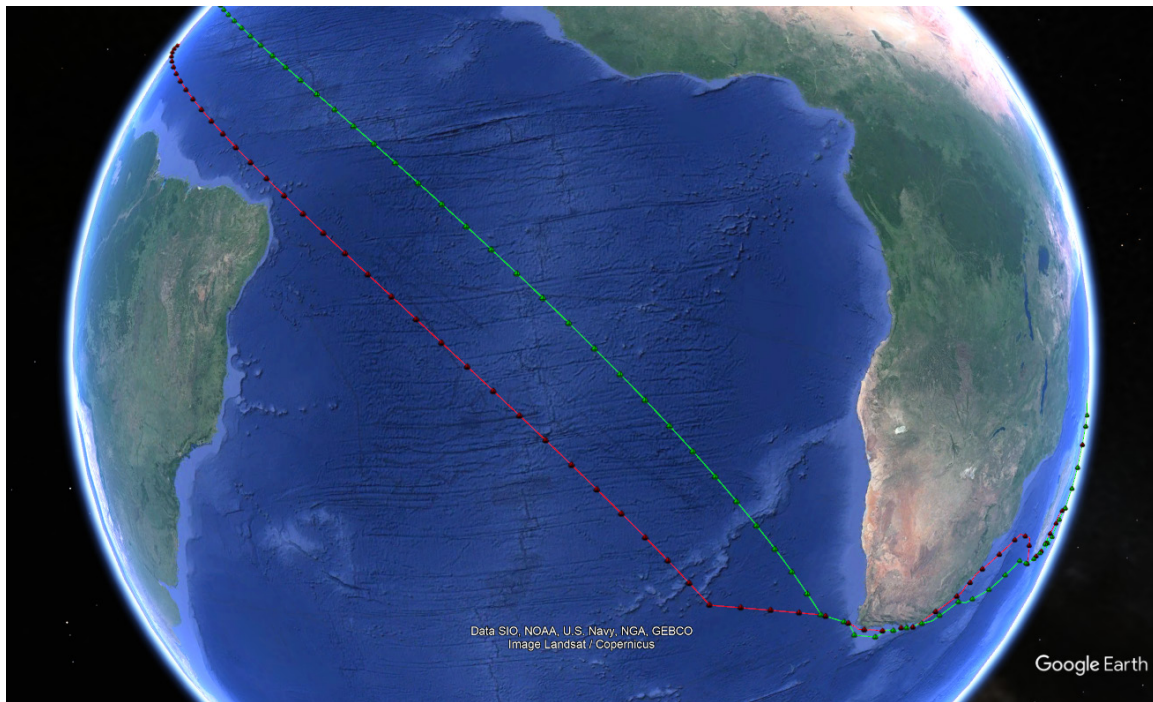


Figure 18. Diego Garcia to Mayport, Florida Regional Route Differences

Given the limited number of ESPC design points that exhibited this behavior, no conclusions could be drawn as to why the routes were further north for this subset. That is, similar design points, including same departure dates and seasons that routed with ESPC, also went along the red route. Additionally, two SE ESPC design points outperformed

legacy and climatology in terms of fuel and time, but the remaining SE ESPC route did not for either metric. Regardless, there is no reason to discard these design points as previously done with the San Diego, CA to Bahrain routes.

The last route we examine in our exploratory data analysis is from Busan, South Korea to San Antonio, Chile. For all 243 design points with this origin/destination pair, 50 were classified as SW while 193 were classified as NW. All 81 ESPC routes, 56 legacy, and 56 climatology routes were NW. A snapshot of the route differences with three design points is provided in Figure 19.

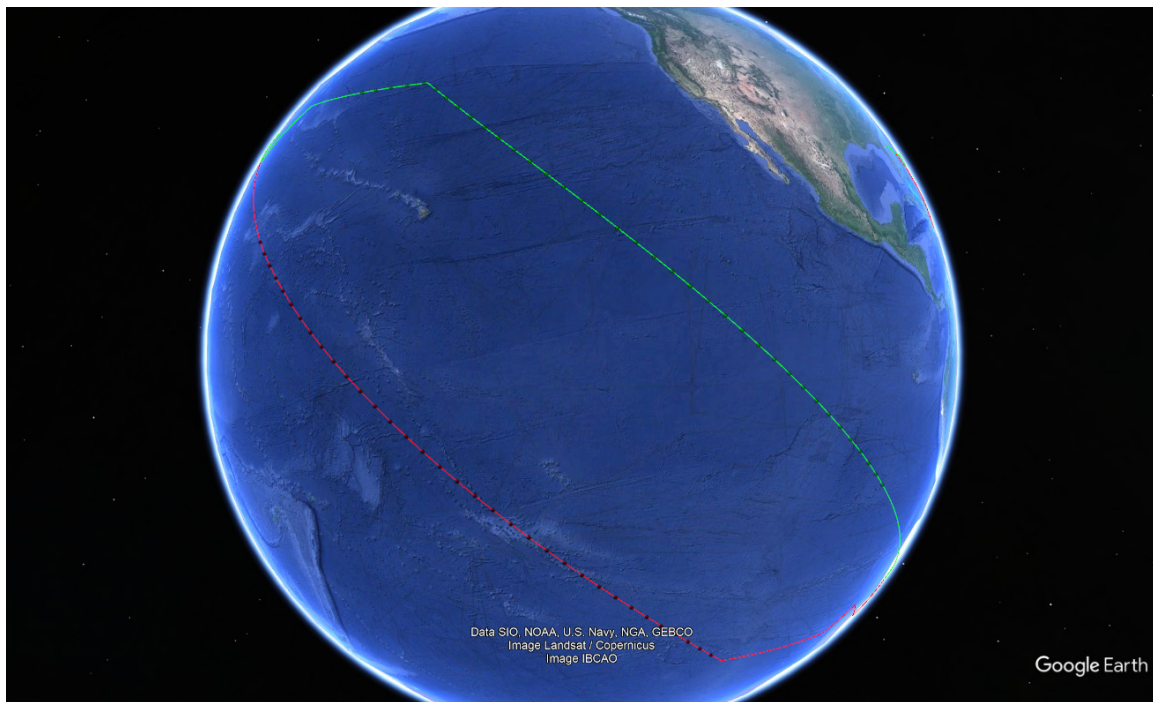
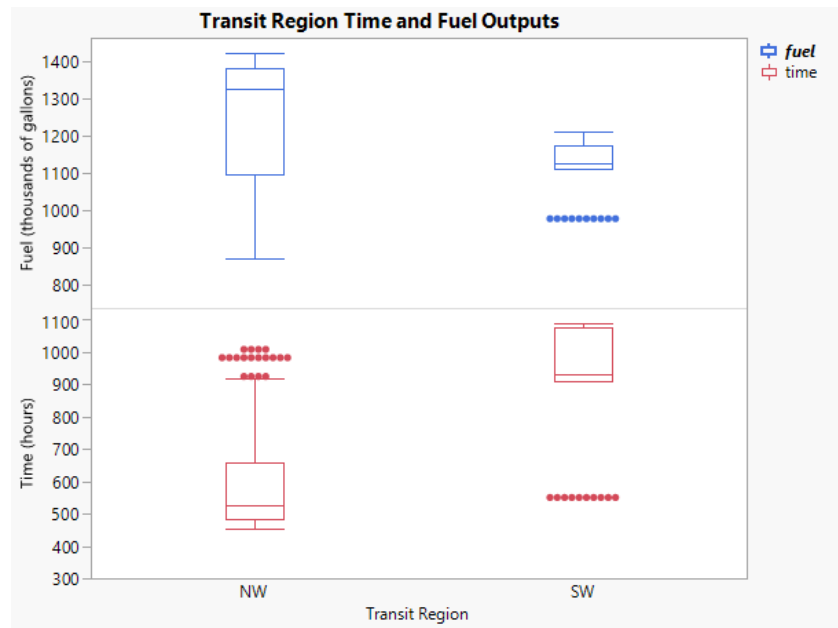


Figure 19. Busan, South Korea to San Antonio, Chile Regional Route Differences

Green represents our NW routes and red represents our SW routes. The differences in route selections are drastic with this origin/destination pair. The box plots shown in Figure 20 suggest that the SW routes tend to save more fuel but take much longer.



Again, there is no reason to discard these design points as previously done with the San Diego, CA to Bahrain routes.

2. Relative ESPC Fuel Consumption in New Design

Summary statistics for ESPC fuel performance relative to legacy and climatology are shown in Figures 21 and 22.

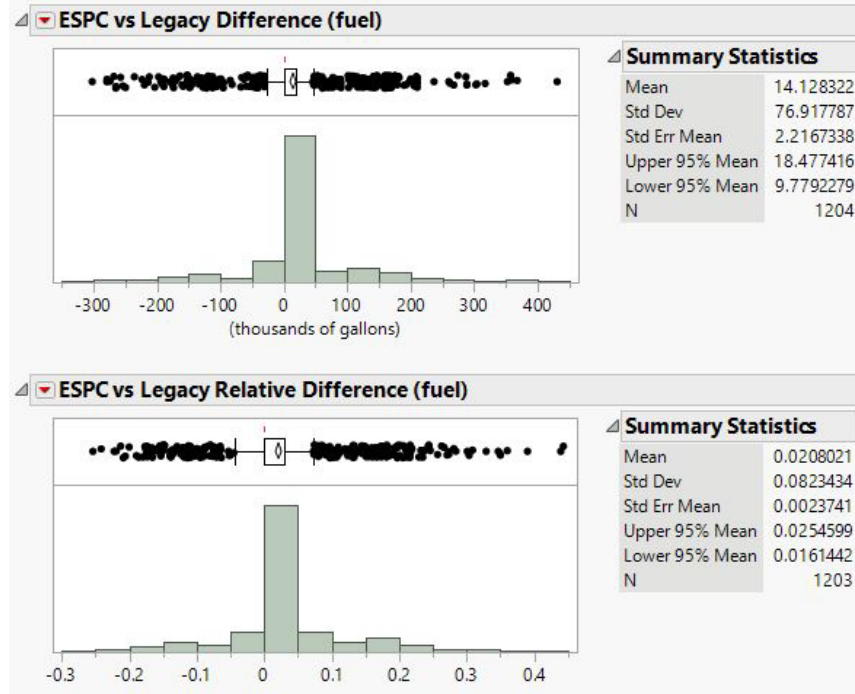


Figure 21. ESPC vs. Legacy Fuel Performance Summary Statistics: Negative Values Indicate Fuel Savings

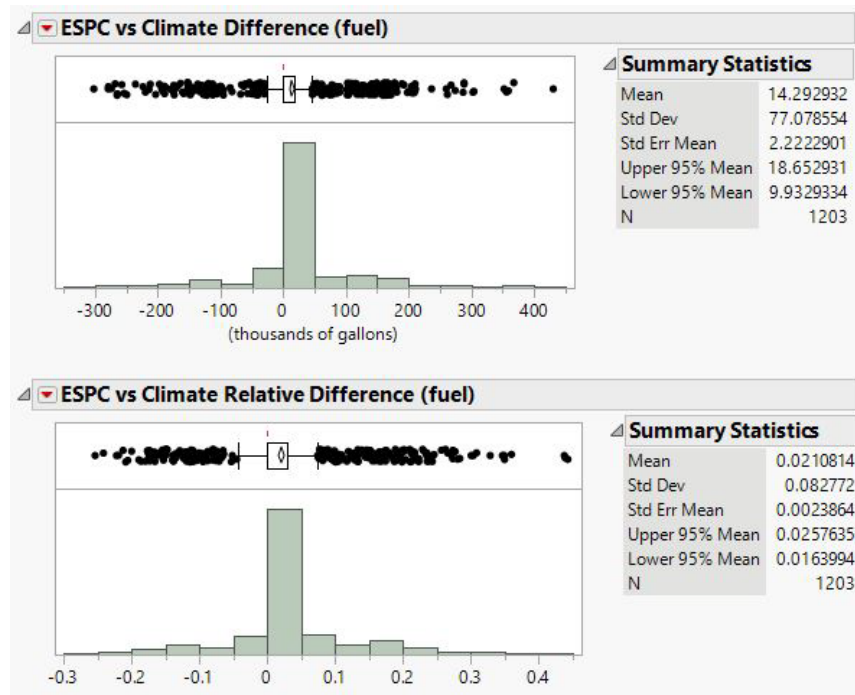


Figure 22. ESPC vs. Climatology Fuel Performance Summary Statistics: Negative Values Indicate Fuel Savings

Our summary statistics indicate that in the overall design, routes generated with ESPC data use about 14,000 more gallons of fuel on average, or about two percent more on average, when compared to the legacy and climatology routes. However, we see significant “ties” or differences of zero for many design points. Figures 23 and 24 show our summary statistics with these “ties” removed.

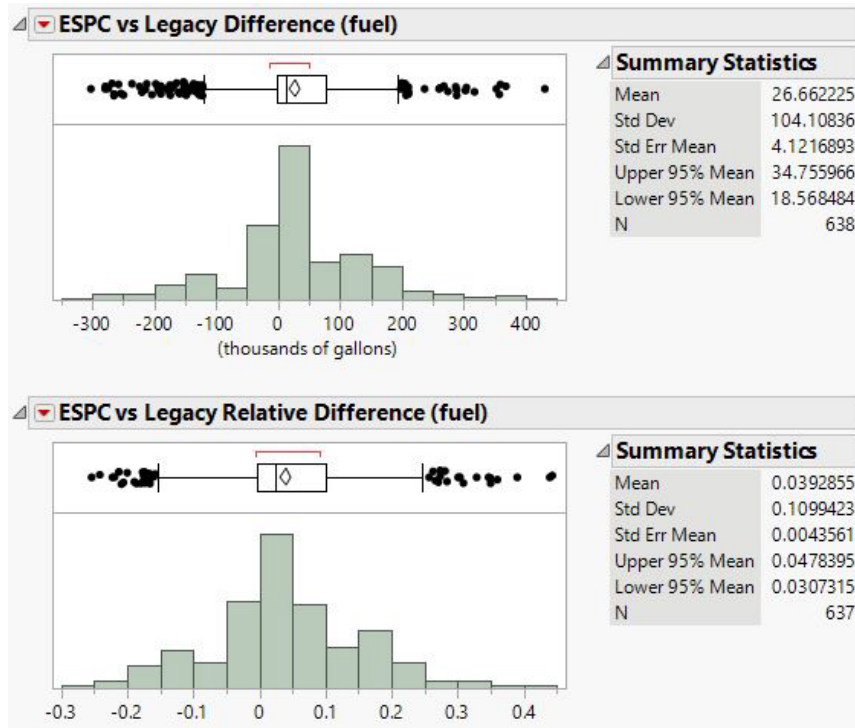


Figure 23. ESPC vs. Legacy Fuel Performance Summary Statistics with Ties Removed: Negative Values Indicate Fuel Savings

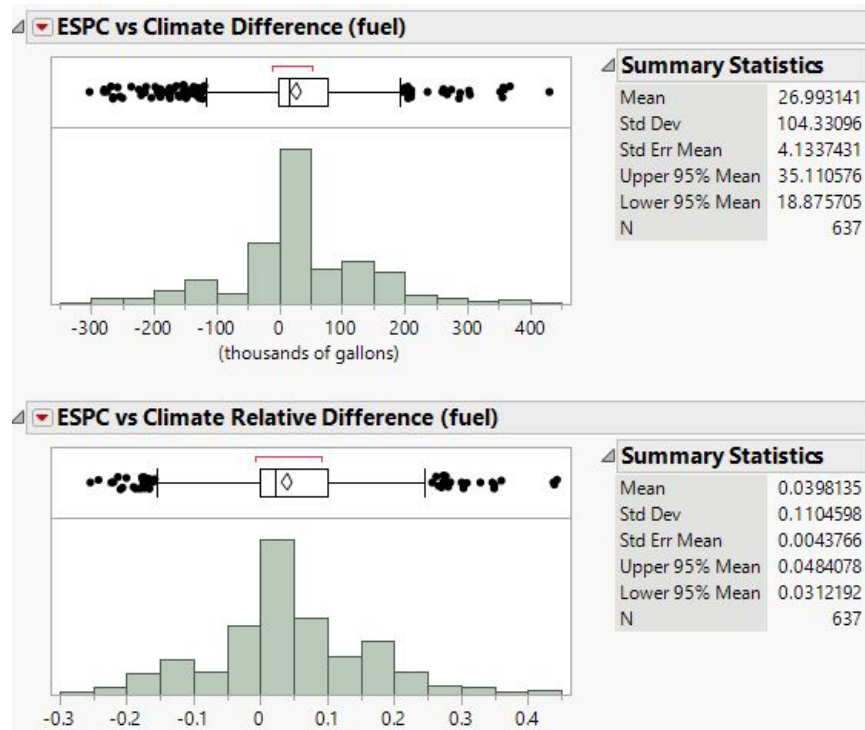


Figure 24. ESPC vs. Climatology Fuel Performance Summary Statistics with Ties Removed: Negative Values Indicate Fuel Savings

With the removal of routes that had equal performance, we see our average fuel consumption for ESPC routes increase to nearly 27,000 more gallons, or four percent on average. Further analysis reveals that most of our “ties” are the result of identical routes being produced when replanning in route in disabled. This can be seen in Figures 25 and 26.

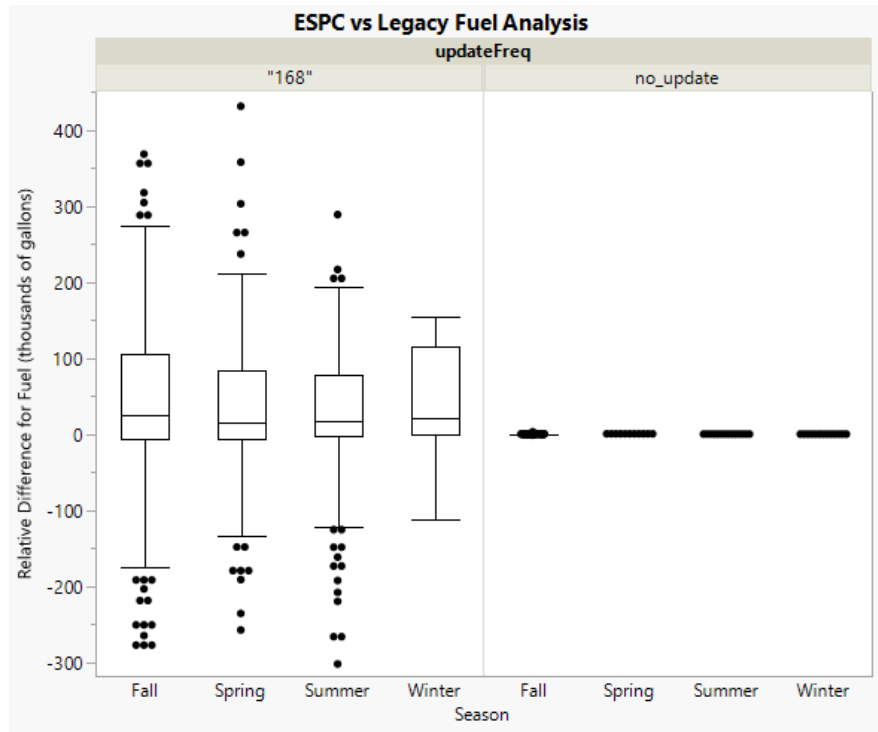


Figure 25. ESPC vs. Legacy Replanning Analysis for Fuel

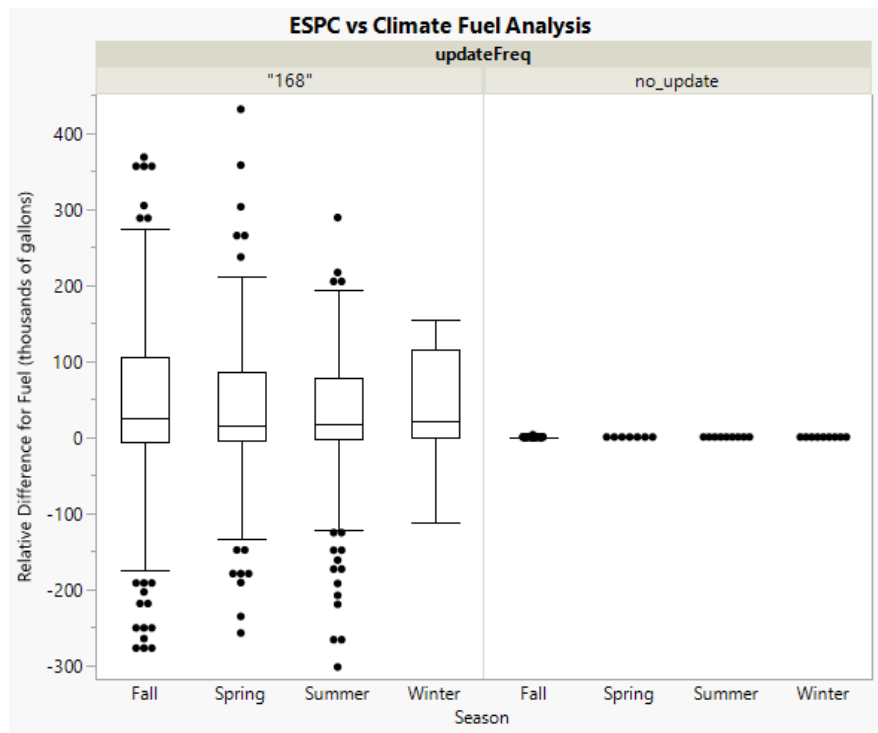


Figure 26. ESPC vs. Climatology Replanning Analysis for Fuel

Verification that TMPLAR was pulling from the correct METOC datasets for our “no_update” design points was conducted to find possible bugs. No bugs were detected. The findings in Figures 25 and 26 are counterintuitive, given that we would expect ESPC to at least outperform climatology when no replanning takes place while enroute. Figure 27 suggests that our route distance significantly affects the variability of fuel output when replanning is enabled. The estimated number of updates enroute is based off our minimum transit times for each port origin/destination pair. That is, the minimum transit time plus the late arrival window is divided using floor division to get the estimated update numbers. More updates indicate that a route is more distant.

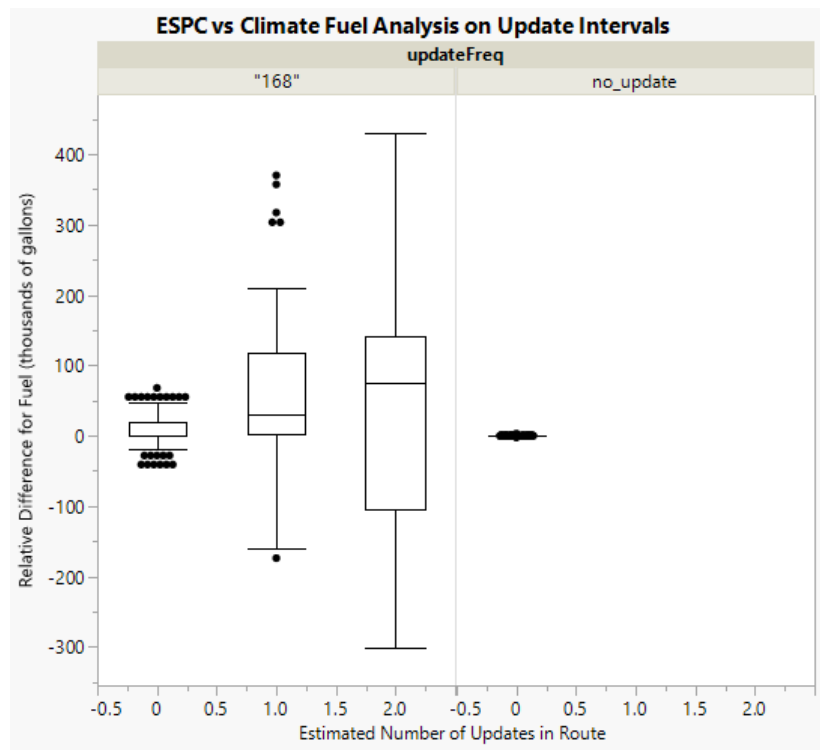


Figure 27. ESPC vs. Climatology Update Interval Analysis

Figure 27 suggests that ESPC performance is much more variable the longer a route is when replanning is enabled. As our estimated number of updates increases, so does the variability of our fuel output.

Regarding ESPC's performance on fuel consumption, the results of this section are inconclusive. On average, our ESPC routes did tend to use more fuel than routes generated with legacy and climatology data. However, we see wide variability in these outputs, with some ESPC routes saving a drastic amount. In terms of overall TMPLAR behavior, it is important to mention that no forecasting system appears to outperform the other when replanning in route is disabled.

3. Relative ESPC Route Times in New Design

Summary statistics for ESPC route duration performance relative to legacy and climatology are shown in Figure 28 and Figure 29.

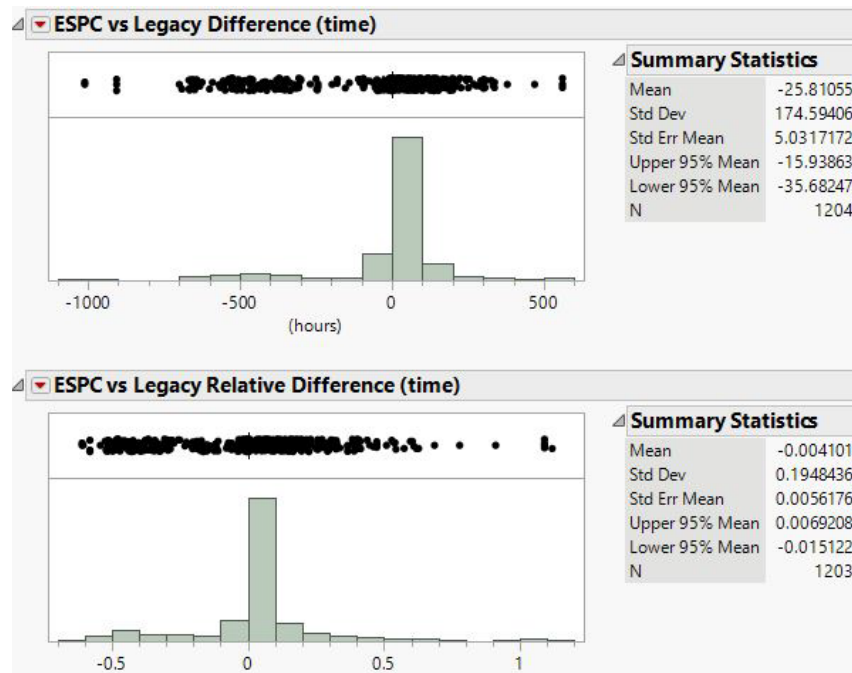


Figure 28. ESPC vs. Legacy Time Performance Summary Statistics: Negative Values Indicate Time Savings



Figure 29. ESPC vs. Climatology Time Performance Summary Statistics:
Negative Values Indicate Time Savings

The summary statistics shown in Figures 28 and 29 suggest that our ESPC routes required nearly 26 hours less transit time compared to the legacy and climatology routes, or around 0.4 percent less on average. Like the analysis conducted in the previous section, we see that there are many design points that experienced “ties,” or had time differences and relative differences of zero. The summary statistics with our “ties” removed can be seen below in Figures 30 and 31.

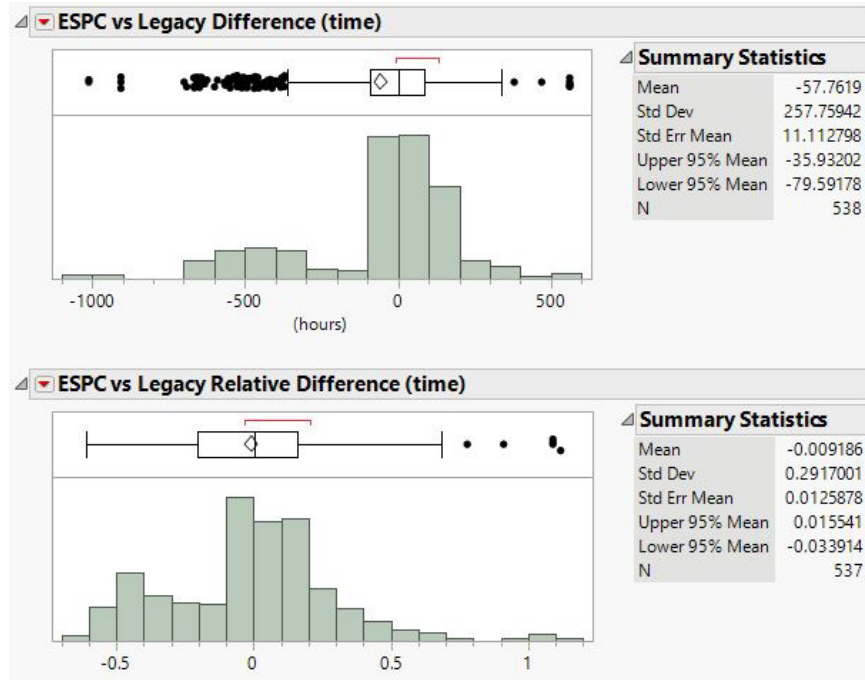


Figure 30. ESPC vs. Legacy Time Performance Summary Statistics with Ties Removed: Negative Values Indicate Time Savings

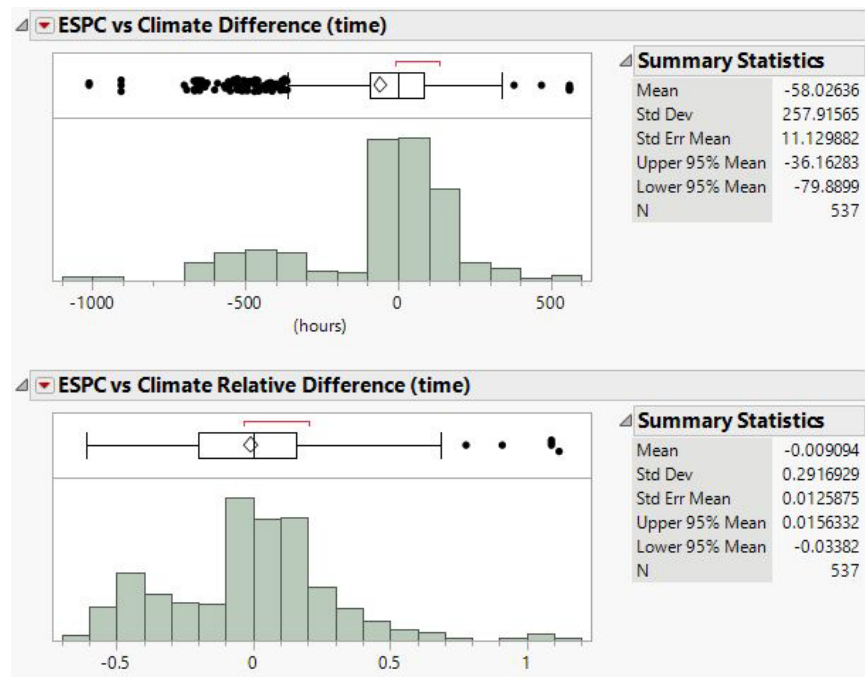


Figure 31. ESPC vs. Climatology Time Performance Summary Statistics with Ties Removed: Negative Values Indicate Time Savings

With the removal of routes that had equal performance, we see that the ESPC routes in our design require about 58 hours less travel time on average, or around 0.9 percent less time, compared to legacy and climatology routes.

Closer analysis of our “ties” reveals that again, when replanning is disabled, we get equal time outputs. This is consistent with our legacy routes as well, since ESPC, legacy, and climatology tend to produce identical routes when replanning is disabled. Figure 32 is provided to visualize this pattern. When planning is enabled, the variability of our time output increases with longer transit distances, as shown in Figure 33. This is consistent with our fuel output findings.

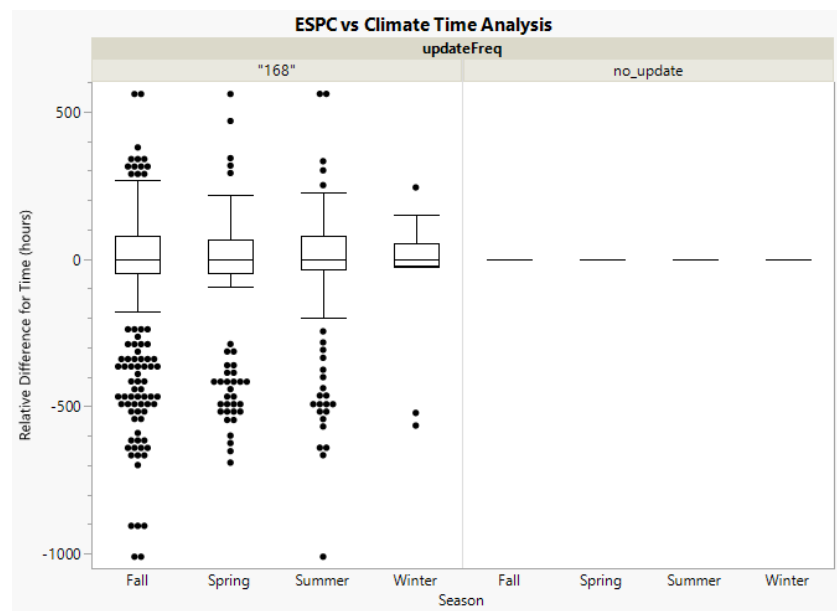


Figure 32. ESPC vs. Climatology Replanning Analysis for Time

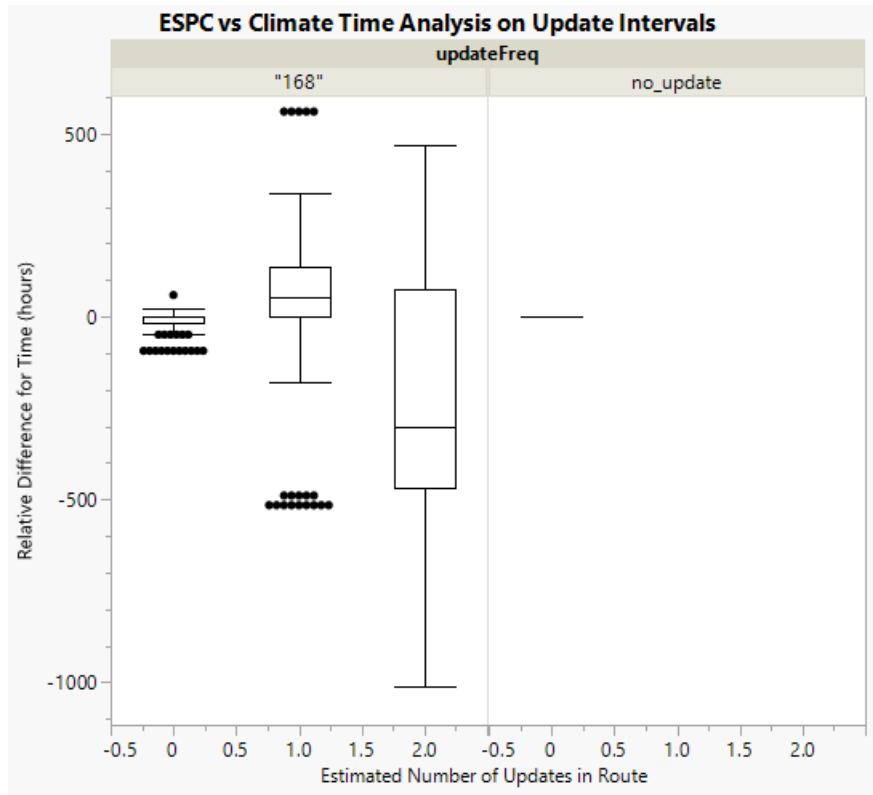


Figure 33. ESPC vs. Climatology Update Interval Analysis for Time

Regarding ESPC's performance on transit times, the results of this section are, again, inconclusive. On average, our ESPC routes did tend to produce routes with shorter travel times than legacy and climatology routes. However, we see wide variability in these outputs, with some ESPC routes requiring much more travel time. In terms of overall TMPLAR behavior, it is important to mention that no forecasting system appears to outperform the other when replanning in route is disabled.

4. Wave Heights in New Design

To conclude the analysis on the routes produced in our new design, we compare the distributions of the maximum wave heights experienced. Figure 34 is provided to demonstrate that no system appears to outperform the other.

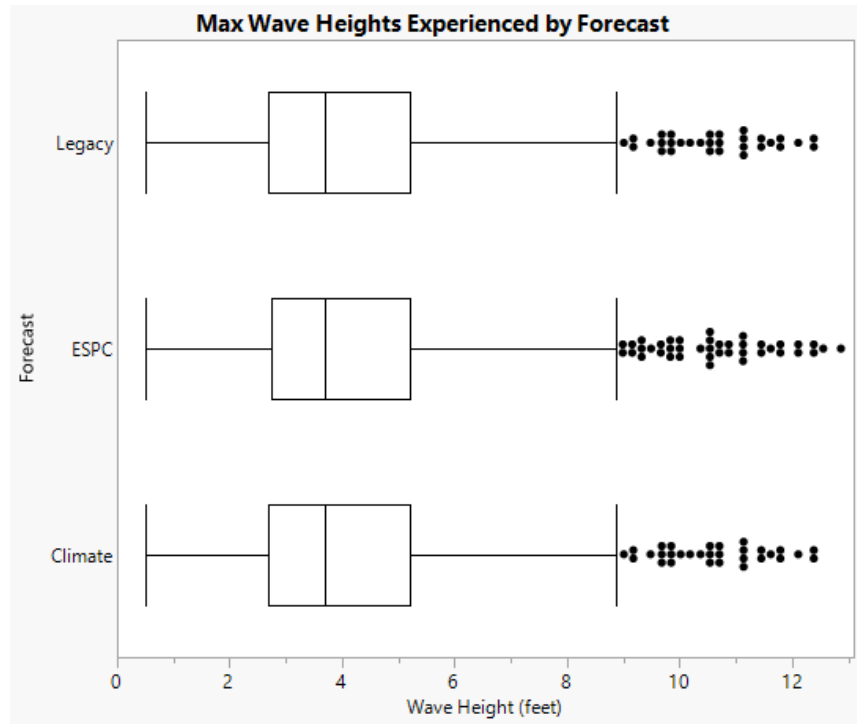


Figure 34. Max Wave Heights Experienced by Forecasting System in New Design

Although the differences in wave heights are not informative, our outliers are. Further analysis of an outlier reveals interesting information about ESPC limitations. In one route, we see the maximum wave height for ESPC is greater than 12 feet. For this outlier, the route is from San Diego, CA to Singapore. By plotting the route in Figure 35, we can visualize where this difference takes place. Note that Figure 35 is about 400 nautical miles south of the Bering Sea.

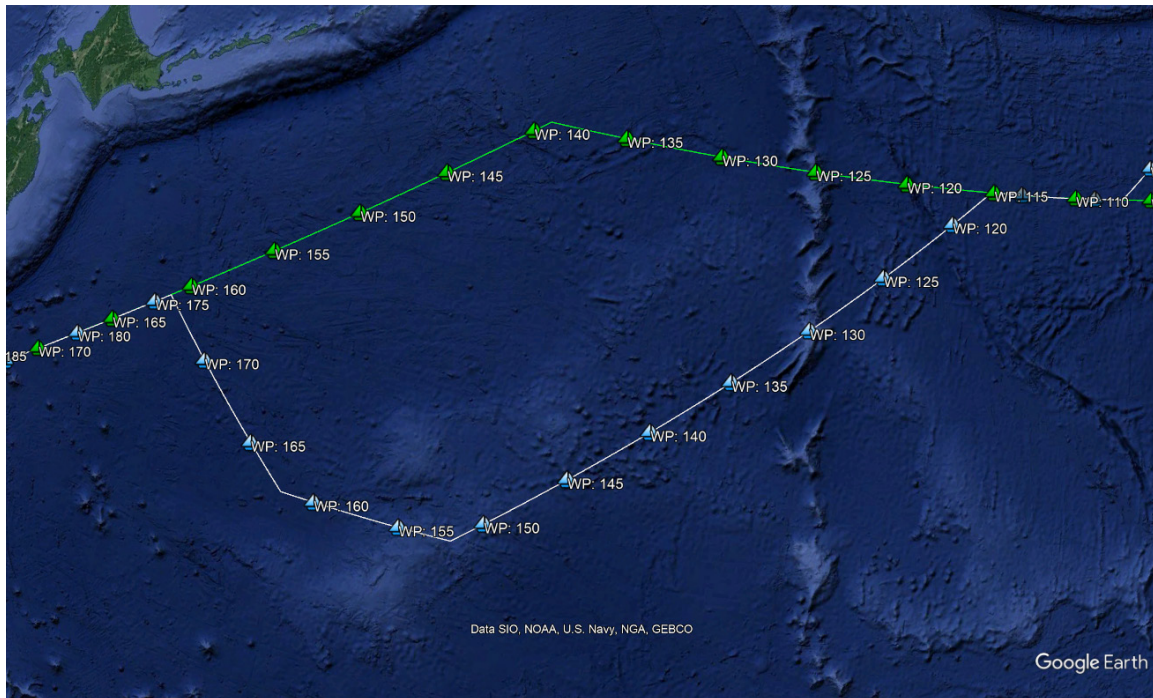


Figure 35. ESPC Route (Northernly Route) Through Rough Sea States

Our northernly route represents ESPC and southernly route represents legacy and climatology. Around waypoints 115, we see drastic route deviation with ESPC from legacy and climatology. Between waypoints 130 and 155 for ESPC, our ship is experiencing waves greater than 10 feet with a maximum height of around 12 feet at waypoint 135. The maximum wave height experienced for southern routes is no greater than four feet. The DTG for ESPC at waypoint 115 is nearly 36 hours behind waypoint 115 for legacy and climatology. This indicates that ESPC was using older forecasting information when it routed us north. Additionally, at waypoint 115 for our ESPC route, we are about 25 hours away from our next forecast update, indicating our METOC information is approximately six days old. We do not receive an update until waypoint 140 when the ship is already facing rough sea states. The key takeaway from this outlier is that the one-week forecasting update for ESPC makes it vulnerable to routing ships into storms. As a result, in this route we use about 300,000 more gallons of fuel with ESPC and arrive at our destination 293 hours after the legacy and climatology routes. This issue is not unique to ESPC itself and

users should be aware that this new system does not exempt TMPLAR routes from the dangers of routing with outdated forecasting information.

D. IMPROVEMENTS IN TMPLAR AS A RESULT OF LARGE-SCALE SIMULATION

Not only was large-scale simulation useful in answering our research question, but its value was also demonstrated by improving the resilience of the TMPLAR algorithm itself. In our early simulation runs prior to those analyzed in Sections A-D, we were able to identify issues with the replanning feature of TMPLAR. In earlier designs, shorter routes with replanning turned on with zero updates in route were producing different results than the same routes with replanning turned off. We knew this was incorrect, given that in both scenarios, no updates would have been made. Thus, TMPLAR should have produced equal route outputs. NRL was quickly able to identify the bug in TMPLAR causing the discrepancy. In later simulation runs, we noticed that all routes constructed with ESPC were identical to routes constructed via climatology. Every detail, including waypoints, fuel usage, time of transit, and max height exposure was identical. We discovered that ESPC data starts at noon while routes started at midnight. When TMPLAR went to pull ESPC data, the system concluded no data existed and defaulted to climatology for the duration of the route. All design points originally departed at midnight and were shifted 12 hours to remedy this issue. Once this issue was addressed, our simulation was run again. Many routes constructed with ESPC were distinct, providing evidence that ESPC had been successfully implemented in TMPLAR. A detailed examination of three runs where the forecasting systems were tied verified that they used different estimates of fuel usage when constructing the routes; the ties occurred because the planned routes were identical which produced the same results when evaluated against ground truth. Finally, through analysis of wave exposure along routes, we detected issues with wave values in our output. Specifically, max wave values were unreasonably high. NRL determined that the wave results were due to old coding techniques used to identify missing values and quickly resolved the issue.

In our quest to answer the research question, the greatest hurdle faced was getting the design to successfully run. A significant portion of time was spent debugging code to

prepare our design, debugging the code to produce input payloads, and improving TMPLAR to meet the needs of this study. The lessons learned and code produced will be provided for future researchers, so more focus can be applied to the analysis of output rather than administrative preparation of the simulation itself.

VII. CONCLUSIONS AND FUTURE WORK

This research sought to answer the following question: does the Navy's new ESPC improve routes generated by TMPLAR relative to other forecast models? The findings of this study are inconclusive when measuring forecasting performance with TMPLAR outputs on fuel usage, travel duration, and wave heights. On average, we see ESPC routes using more fuel, requiring less time, and experiencing similar wave conditions as our legacy and climatology systems. However, the variability of our output makes the determination of forecasting system dominance inappropriate. More research is required.

The most significant contribution this research provides is insight into overall TMPLAR behavior. First, single-objective routing in TMPLAR for fuel minimization is not recommended for military operations that are time sensitive. We see significant fuel savings when fuel is minimized vice time/distance, but our desired arrival time windows are not honored. Specifically, in our first design, we saw ships arrive five days late on average. Routes minimized for fuel and constructed with ESPC data tend to arrive at their destinations the "least late" compared to legacy and climatology routes also minimized for fuel. Second, TMPLAR is highly sensitive to port coordinates that are close to land. Locations too close to land cause errors in the algorithm and routes are often not produced. Planners may have to adjust port locations further offshore for TMPLAR to successfully run. Third, when constructing routes with replanning disabled, routes are almost always identical, regardless of which forecasting system is used. It is only when replanning is enabled that we see variability in TMPLAR outputs. Finally, TMPLAR is not exempt from the dangers of routing with outdated METOC information. Our simulation revealed a scenario where a ship was routed into rough sea states due to outdated environmental forecast information. Planners should be aware of the potential hazards they face when routing with outdated environmental forecasts.

The value of simulation in reaching these conclusions cannot be understated. A real-world, large-scale experiment with TMPLAR would come at a great cost in terms of time and money. Learning these lessons with actual fleet operations could be dangerous as well, depending on the environmental conditions faced by actual ships. While our results

regarding ESPC performance in TMPLAR are inconclusive, the value gained in improving TMPLAR robustness is significant.

A. FUTURE WORK

Immediate future work involves collecting more ESPC data to cover full seasonal variability (ESPC dates for this study were predominantly for the fall and spring months) and modifying port locations in the original design to get all design points to run. Also, future research into the identical TMPLAR outputs when replanning is disabled would be useful. It is counterintuitive that climatology would perform just as well as ESPC and legacy, especially for our shorter routes. Furthermore, recall that this research used ship parameters based solely on the DDG-51 Guided Missile Destroyer. Additional studies with alternative ship data would be useful to understand TMPLAR behavior with different naval assets. Finally, future work to examine TMPLAR performance in routing ships through known storms would be useful. This research has shown that ESPC is not exempt from catastrophic routing into storms with outdated METOC information. Designing an experiment that focuses solely on poor METOC conditions would be useful in gaining insight into how ESPC performs relative to legacy and climatology systems.

B. CONCLUDING THOUGHTS

TMPLAR is a powerful tool that will have significant impacts on U.S. Navy operations in the future. While the findings of this study regarding ESPC performance are inconclusive, the scenarios (design points) ingested by TMPLAR have significantly matured the algorithm in a short span of time. This research is yet another example of the value that large scale simulation can provide in terms of efficiency, cost, and safety relative to any real-world study.

APPENDIX A. MINIMUM TRANSIT TIMES

Locations	Anchorage	Bahrain	Busan, So	Cape Tow	Diego Gar	Guam	Manila, Ph	Mayport, I	Naples, It	Norfolk, U	Okinawa	Pearl Har	Rota, Spai	San Anton	San Diego	Sao Luis, E	Singapore	Souda Bay	Sydney, A	Trondheim
Anchorage, Alaska		549.8	159.2	427.6	477.1	150.4	218.5	546.5	622.3	547.4	168.3	89.3	575.9	242.6	83.6	458.6	253.1	639.8	266.8	228.1
Bahrain	549.8		463.1	243.6	64.2	402.1	212.1	444.9	473.5	445.3	442.3	425	435.6	422.7	482.6	369.5	175.9	491	268.8	481
Busan, South Korea	159.2	463.1		474.3	399.1	63.5	67.8	596.4	672.2	596.8	21.3	156.8	625.8	356.6	204.5	512.9	94.2	689.7	201.5	244.2
Cape Town, South Africa	427.6	243.6	474.3		167.8	438.5	256.7	219.4	247.9	219.8	474.1	346.3	210.1	207.9	368.2	140.1	220.3	265.5	251.2	255.4
Diego Garcia	477.1	64.2	399.1	167.8		339.7	149.7	382.7	411.2	383.1	379.9	362.6	373.3	360.3	410.8	307.3	113.3	428.7	206.2	418.7
Guam	150.4	402.1	63.5	438.5	339.7		73	560.1	636.5	560.5	42.9	126.7	590.2	311.4	192	476.1	102.4	654	142.5	260.2
Manila, Philippines	218.5	212.1	67.8	256.7	149.7	73		631.2	493.5	631.6	48.5	191.6	455.7	388.2	239.3	547.2	41.9	511.1	205.7	278.5
Mayport, Florida	546.5	444.9	596.4	219.4	382.7	560.1	631.2		171	33.3	613.8	471	129.1	318.9	463	108.6	426	188.5	452.8	133.3
Naples, Italy	622.3	473.5	672.2	247.9	411.2	636.5	493.5	171		150	654.9	529.2	35.4	376.8	521.1	157.2	454.6	32.9	493.1	114.8
Norfolk, Virginia	547.4	445.3	596.8	219.8	383.1	560.5	631.6	33.3	150		613.9	471.1	113.6	318	463	107.8	426	173.1	451.9	117.9
Okinawa, Japan	168.3	442.3	21.3	474.1	379.9	42.9	48.5	613.8	654.9	613.9		157.4	628	353.7	205	515	74.3	691.9	178.7	246.3
Pearl Harbor, Hawaii	89.3	425	156.8	346.3	362.6	126.7	191.6	471	529.2	471.1	157.4		501.9	198.9	78.6	384.6	235.2	565.7	180.1	557.2
Rota, Spain	575.9	435.6	625.8	210.1	373.3	590.2	455.7	129.1	35.4	113.6	628	501.9		340.7	484.4	121.1	417.2	55.4	456.4	78.1
San Antonio, Chile	242.6	422.7	356.6	207.9	360.3	311.4	388.2	318.9	376.8	318	353.7	198.9	340.7		172.7	230	432.2	411.1	231.4	405.4
San Diego, California	83.6	482.6	204.5	368.2	410.8	192	239.3	463	521.1	463	205	78.6	484.4	172.7		389.8	320.3	571.2	226	549.1
Sao Luis, Brazil	458.6	369.5	512.9	140.1	307.3	476.1	547.2	108.6	157.2	107.8	515	384.6	121.1	230	389.8		345.4	184.9	372.6	160.8
Singapore	253.1	175.9	94.2	220.3	113.3	102.4	41.9	426	454.6	426	74.3	235.2	417.2	432.2	320.3	345.4		472.3	232	461.7
Souda Bay, Greece	639.8	491	689.7	265.5	428.7	654	511.1	188.5	32.9	173.1	691.9	565.7	55.4	411.1	571.2	184.9	472.3		514.1	132.6
Sydney, Australia	266.8	268.8	201.5	251.2	206.2	142.5	205.7	452.8	493.1	451.9	178.7	180.1	456.4	231.4	226	372.6	232	514.1		520.9
Trondheim, Norway	228.1	481	244.2	255.4	418.7	260.2	278.5	133.3	114.8	117.9	246.3	557.2	78.1	405.4	549.1	160.8	461.7	132.6	520.9	

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APPENDIX B. ROUTES FROM ORIGINAL DESIGN

Origin	Destination	StartDtg	EndDtg
Sydney, Australia	Busan, South Korea	2020-12-20T12:01:00.000Z	2021-01-01T21:31:00.000Z
Singapore	Sydney, Australia	2020-10-18T12:01:00.000Z	2020-11-01T04:01:00.000Z
Singapore	Naples, Italy	2021-09-19T12:01:00.000Z	2021-10-12T10:37:00.000Z
Trondheim, Norway	Singapore	2021-10-10T12:01:00.000Z	2021-11-02T17:43:00.000Z
Souda Bay, Greece	Bahrain	2020-12-20T12:01:00.000Z	2021-01-13T23:01:00.000Z
Rota, Spain	Norfolk, USA	2021-10-03T12:01:00.000Z	2021-10-12T05:37:00.000Z
Okinawa, Japan	Rota, Spain	2021-10-03T12:01:00.000Z	2021-11-02T16:01:00.000Z
Pearl Harbor, USA	Guam	2020-11-01T12:01:00.000Z	2020-11-10T18:43:00.000Z
San Antonio, Chile	Pearl Harbor, USA	2020-11-15T12:01:00.000Z	2020-11-27T18:55:00.000Z
San Antonio, Chile	Diego Garcia	2021-08-22T12:01:00.000Z	2021-09-10T12:19:00.000Z
San Diego, USA	San Antonio, Chile	2021-04-18T12:01:00.000Z	2021-04-29T16:43:00.000Z
Trondheim, Norway	Cape Town, South Africa	2020-10-27T12:01:00.000Z	2020-11-11T03:25:00.000Z
Sao Luis, Brazil	Trondheim, Norway	2020-12-06T12:01:00.000Z	2020-12-17T04:49:00.000Z
Pearl Harbor, USA	Diego Garcia	2021-09-12T12:01:00.000Z	2021-10-01T14:37:00.000Z
San Diego, USA	Pearl Harbor, USA	2021-04-11T12:01:00.000Z	2021-04-18T18:37:00.000Z
Anchorage, Alaska	Singapore	2021-04-04T12:01:00.000Z	2021-04-19T01:07:00.000Z
Busan, South Korea	Anchorage, Alaska	2021-09-12T12:01:00.000Z	2021-09-23T03:13:00.000Z
Busan, South Korea	Trondheim, Norway	2020-10-11T12:01:00.000Z	2020-10-25T16:13:00.000Z
Naples, Italy	Busan, South Korea	2020-09-27T12:01:00.000Z	2020-10-29T12:13:00.000Z
Bahrain	Souda Bay, Greece	2021-04-04T12:01:00.000Z	2021-04-28T23:01:00.000Z
Manila, Philippines	Okinawa, Japan	2020-10-04T12:01:00.000Z	2020-10-10T12:31:00.000Z
Norfolk, USA	Manila, Philippines	2020-10-04T12:01:00.000Z	2020-11-03T19:37:00.000Z
Mayport, USA	San Antonio, Chile	2021-08-22T12:01:00.000Z	2021-09-08T18:55:00.000Z

Origin	Destination	StartDtg	EndDtg
Guam	Mayport, USA	2021-08-15T12:01:00.000Z	2021-09-11T20:07:00.000Z
Guam	San Diego, USA	2020-11-15T12:01:00.000Z	2020-11-27T12:01:00.000Z
Diego Garcia	Guam	2020-12-06T12:01:00.000Z	2020-12-24T15:43:00.000Z
Naples, Italy	Sao Luis, Brazil	2021-09-05T12:01:00.000Z	2021-09-16T01:13:00.000Z
Cape Town, South Africa	Naples, Italy	2021-04-18T12:01:00.000Z	2021-05-02T19:55:00.000Z
Mayport, USA	San Diego, USA	2020-10-18T12:01:00.000Z	2020-11-10T19:01:00.000Z
Diego Garcia	Mayport, USA	2020-12-13T12:01:00.000Z	2021-01-02T10:43:00.000Z
Busan, South Korea	Naples, Italy	2020-10-27T12:01:00.000Z	2020-11-28T12:13:00.000Z
Sydney, Australia	Busan, South Korea	2020-12-06T12:01:00.000Z	2020-12-18T21:31:00.000Z
Naples, Italy	Singapore	2020-10-18T12:01:00.000Z	2020-11-10T10:37:00.000Z
Singapore	Sydney, Australia	2020-12-13T12:01:00.000Z	2020-12-27T04:01:00.000Z
Bahrain	Norfolk, USA	2020-11-01T12:01:00.000Z	2020-11-24T01:19:00.000Z
Souda Bay, Greece	Manila, Philippines	2020-11-15T12:01:00.000Z	2020-12-10T19:07:00.000Z
Norfolk, USA	Souda Bay, Greece	2020-11-15T12:01:00.000Z	2020-11-26T17:07:00.000Z
Rota, Spain	Souda Bay, Greece	2020-12-06T12:01:00.000Z	2020-12-12T19:25:00.000Z
Guam	Diego Garcia	2021-04-04T12:01:00.000Z	2021-04-22T15:43:00.000Z
Pearl Harbor, USA	Guam	2021-04-25T12:01:00.000Z	2021-05-04T18:43:00.000Z
Diego Garcia	San Antonio, Chile	2021-10-03T12:01:00.000Z	2021-10-22T12:19:00.000Z
San Antonio, Chile	Pearl Harbor, USA	2021-10-03T12:01:00.000Z	2021-10-15T18:55:00.000Z
Cape Town, South Africa	Diego Garcia	2021-04-04T12:01:00.000Z	2021-04-15T11:49:00.000Z
Trondheim, Norway	Mayport, USA	2021-09-12T12:01:00.000Z	2021-09-22T01:19:00.000Z
Diego Garcia	Sao Luis, Brazil	2021-09-19T12:01:00.000Z	2021-10-06T07:19:00.000Z
Pearl Harbor, USA	Trondheim, Norway	2021-10-10T12:01:00.000Z	2021-11-06T17:13:00.000Z
Singapore	Trondheim, Norway	2021-09-05T12:01:00.000Z	2021-09-28T17:43:00.000Z

Origin	Destination	StartDtg	EndDtg
Anchorage, Alaska	Singapore	2021-04-18T12:01:00.000Z	2021-05-03T01:07:00.000Z
Trondheim, Norway	Busan, South Korea	2021-09-12T12:01:00.000Z	2021-09-26T16:13:00.000Z
Busan, South Korea	Anchorage, Alaska	2021-04-11T12:01:00.000Z	2021-04-22T03:13:00.000Z
Souda Bay, Greece	Okinawa, Japan	2021-08-22T12:01:00.000Z	2021-09-24T07:55:00.000Z
Bahrain	Rota, Spain	2021-08-15T12:01:00.000Z	2021-09-06T15:37:00.000Z
Okinawa, Japan	Bahrain	2021-08-22T12:01:00.000Z	2021-09-13T22:19:00.000Z
Manila, Philippines	Bahrain	2021-04-18T12:01:00.000Z	2021-05-01T08:07:00.000Z
San Antonio, Chile	San Diego, USA	2020-12-20T12:01:00.000Z	2020-12-31T16:43:00.000Z
Mayport, USA	San Antonio, Chile	2020-11-29T12:01:00.000Z	2020-12-16T18:55:00.000Z
San Diego, USA	Guam	2020-10-04T12:01:00.000Z	2020-10-16T12:01:00.000Z
Guam	Mayport, USA	2020-10-04T12:01:00.000Z	2020-10-31T20:07:00.000Z
Sao Luis, Brazil	San Diego, USA	2020-12-20T12:01:00.000Z	2021-01-09T17:49:00.000Z
Naples, Italy	Pearl Harbor, USA	2020-10-18T12:01:00.000Z	2020-11-13T13:13:00.000Z
San Diego, USA	Cape Town, South Africa	2020-10-11T12:01:00.000Z	2020-10-30T20:13:00.000Z
Mayport, USA	Naples, Italy	2020-09-27T12:01:00.000Z	2020-10-08T15:01:00.000Z
Naples, Italy	Diego Garcia	2021-09-12T12:01:00.000Z	2021-10-03T15:13:00.000Z
Busan, South Korea	Mayport, USA	2020-12-20T12:01:00.000Z	2021-01-18T08:25:00.000Z
Singapore	Cape Town, South Africa	2020-10-04T12:01:00.000Z	2020-10-17T16:19:00.000Z
Sydney, Australia	Naples, Italy	2021-10-03T12:01:00.000Z	2021-10-28T01:07:00.000Z
Norfolk, USA	Diego Garcia	2021-04-25T12:01:00.000Z	2021-05-15T11:07:00.000Z
Manila, Philippines	Guam	2020-12-20T12:01:00.000Z	2020-12-27T13:01:00.000Z
Souda Bay, Greece	Guam	2020-09-27T12:01:00.000Z	2020-10-28T18:01:00.000Z
Souda Bay, Greece	Mayport, USA	2021-09-19T12:01:00.000Z	2021-10-01T08:31:00.000Z
Diego Garcia	Okinawa, Japan	2021-08-15T12:01:00.000Z	2021-09-04T07:55:00.000Z

Origin	Destination	StartDtg	EndDtg
Guam	Rota, Spain	2020-11-01T12:01:00.000Z	2020-11-30T02:13:00.000Z
San Antonio, Chile	Souda Bay, Greece	2020-12-06T12:01:00.000Z	2020-12-27T15:07:00.000Z
Pearl Harbor, USA	Souda Bay, Greece	2021-08-22T12:01:00.000Z	2021-09-19T01:43:00.000Z
Diego Garcia	Trondheim, Norway	2021-04-11T12:01:00.000Z	2021-05-02T22:43:00.000Z
Mayport, USA	Singapore	2020-10-18T12:01:00.000Z	2020-11-09T06:01:00.000Z
Sao Luis, Brazil	Singapore	2020-12-06T12:01:00.000Z	2020-12-24T21:25:00.000Z
Trondheim, Norway	Sydney, Australia	2021-09-05T12:01:00.000Z	2021-10-01T04:55:00.000Z
Trondheim, Norway	San Diego, USA	2020-10-18T12:01:00.000Z	2020-11-14T09:07:00.000Z
Singapore	Pearl Harbor, USA	2021-04-04T12:01:00.000Z	2021-04-18T07:13:00.000Z
Busan, South Korea	Sao Luis, Brazil	2021-10-03T12:01:00.000Z	2021-10-28T20:55:00.000Z
Anchorage, Alaska	Trondheim, Norway	2020-10-04T12:01:00.000Z	2020-10-18T00:07:00.000Z
Okinawa, Japan	San Diego, USA	2020-11-29T12:01:00.000Z	2020-12-12T01:01:00.000Z
Rota, Spain	San Antonio, Chile	2021-04-04T12:01:00.000Z	2021-04-22T16:43:00.000Z
Bahrain	San Antonio, Chile	2021-10-10T12:01:00.000Z	2021-11-01T02:43:00.000Z
Bahrain	Pearl Harbor, USA	2020-10-11T12:01:00.000Z	2020-11-02T05:01:00.000Z
San Diego, USA	Norfolk, USA	2020-11-15T12:01:00.000Z	2020-12-08T19:01:00.000Z
San Antonio, Chile	Manila, Philippines	2021-08-22T12:01:00.000Z	2021-09-11T16:13:00.000Z
Guam	Bahrain	2021-04-18T12:01:00.000Z	2021-05-09T06:07:00.000Z
Mayport, USA	Bahrain	2020-11-15T12:01:00.000Z	2020-12-08T00:55:00.000Z
San Diego, USA	Naples, Italy	2020-12-13T12:01:00.000Z	2021-01-08T05:07:00.000Z
Pearl Harbor, USA	Busan, South Korea	2021-09-12T12:01:00.000Z	2021-09-23T00:49:00.000Z
Cape Town, South Africa	Busan, South Korea	2021-04-18T12:01:00.000Z	2021-05-12T06:19:00.000Z
Naples, Italy	Anchorage, Alaska	2020-10-27T12:01:00.000Z	2020-11-26T10:19:00.000Z
Diego Garcia	Singapore	2021-04-18T12:01:00.000Z	2021-04-27T05:19:00.000Z

Origin	Destination	StartDtg	EndDtg
Mayport, USA	Norfolk, USA	2020-10-27T12:01:00.000Z	2020-11-01T21:19:00.000Z
Cape Town, South Africa	Bahrain	2021-04-11T12:01:00.000Z	2021-04-25T15:37:00.000Z
Naples, Italy	Souda Bay, Greece	2020-10-18T12:01:00.000Z	2020-10-23T20:55:00.000Z
Diego Garcia	Rota, Spain	2021-08-15T12:01:00.000Z	2021-09-04T01:19:00.000Z
Guam	Naples, Italy	2020-11-01T12:01:00.000Z	2020-12-02T00:31:00.000Z
Guam	Anchorage, Alaska	2021-04-18T12:01:00.000Z	2021-04-28T18:25:00.000Z
Mayport, USA	Singapore	2020-11-15T12:01:00.000Z	2020-12-07T06:01:00.000Z
Okinawa, Japan	San Antonio, Chile	2020-11-29T12:01:00.000Z	2020-12-18T05:43:00.000Z
Rota, Spain	Diego Garcia	2021-04-04T12:01:00.000Z	2021-04-24T01:19:00.000Z
Souda Bay, Greece	Mayport, USA	2020-10-04T12:01:00.000Z	2020-10-16T08:31:00.000Z
Souda Bay, Greece	San Antonio, Chile	2021-10-03T12:01:00.000Z	2021-10-24T15:07:00.000Z
Singapore	Cape Town, South Africa	2021-04-04T12:01:00.000Z	2021-04-17T16:19:00.000Z
Singapore	Mayport, USA	2020-09-27T12:01:00.000Z	2020-10-19T06:01:00.000Z
Sydney, Australia	San Diego, USA	2021-09-19T12:01:00.000Z	2021-10-02T22:01:00.000Z
San Diego, USA	Busan, South Korea	2020-12-06T12:01:00.000Z	2020-12-19T00:31:00.000Z
Pearl Harbor, USA	Okinawa, Japan	2021-09-05T12:01:00.000Z	2021-09-16T01:25:00.000Z
Sao Luis, Brazil	Souda Bay, Greece	2020-12-13T12:01:00.000Z	2020-12-25T04:55:00.000Z
Trondheim, Norway	Bahrain	2021-09-12T12:01:00.000Z	2021-10-06T13:01:00.000Z
San Diego, USA	Manila, Philippines	2020-11-15T12:01:00.000Z	2020-11-29T11:19:00.000Z
San Antonio, Chile	Trondheim, Norway	2021-08-22T12:01:00.000Z	2021-09-12T09:25:00.000Z
San Antonio, Chile	Sydney, Australia	2020-12-06T12:01:00.000Z	2020-12-20T03:25:00.000Z
Pearl Harbor, USA	Busan, South Korea	2021-08-22T12:01:00.000Z	2021-09-02T00:49:00.000Z
Norfolk, USA	Guam	2021-04-25T12:01:00.000Z	2021-05-22T20:31:00.000Z
Manila, Philippines	San Diego, USA	2020-12-20T12:01:00.000Z	2021-01-03T11:19:00.000Z

Origin	Destination	StartDtg	EndDtg
Bahrain	Pearl Harbor, USA	2021-10-03T12:01:00.000Z	2021-10-25T05:01:00.000Z
Bahrain	Guam	2020-10-04T12:01:00.000Z	2020-10-25T06:07:00.000Z
Busan, South Korea	Sao Luis, Brazil	2020-12-20T12:01:00.000Z	2021-01-14T20:55:00.000Z
Busan, South Korea	Pearl Harbor, USA	2021-10-10T12:01:00.000Z	2021-10-21T00:49:00.000Z
Anchorage, Alaska	Diego Garcia	2020-10-11T12:01:00.000Z	2020-11-04T09:07:00.000Z
Singapore	Pearl Harbor, USA	2021-04-25T12:01:00.000Z	2021-05-09T07:13:00.000Z
Norfolk, USA	Diego Garcia	2021-08-22T12:01:00.000Z	2021-09-11T11:07:00.000Z
Bahrain	Trondheim, Norway	2021-08-15T12:01:00.000Z	2021-09-08T13:01:00.000Z
Souda Bay, Greece	Cape Town, South Africa	2021-09-05T12:01:00.000Z	2021-09-20T13:31:00.000Z
Rota, Spain	San Antonio, Chile	2020-12-13T12:01:00.000Z	2020-12-31T16:43:00.000Z
Naples, Italy	Diego Garcia	2020-10-18T12:01:00.000Z	2020-11-08T15:13:00.000Z
Anchorage, Alaska	Pearl Harbor, USA	2020-12-06T12:01:00.000Z	2020-12-14T05:19:00.000Z
Singapore	Guam	2020-11-01T12:01:00.000Z	2020-11-09T18:25:00.000Z
San Antonio, Chile	Manila, Philippines	2020-09-27T12:01:00.000Z	2020-10-17T16:13:00.000Z
Diego Garcia	Okinawa, Japan	2020-10-11T12:01:00.000Z	2020-10-31T07:55:00.000Z
Mayport, USA	Bahrain	2020-10-18T12:01:00.000Z	2020-11-10T00:55:00.000Z
San Antonio, Chile	Souda Bay, Greece	2020-12-20T12:01:00.000Z	2021-01-10T15:07:00.000Z
Trondheim, Norway	Busan, South Korea	2021-10-03T12:01:00.000Z	2021-10-17T16:13:00.000Z
Cape Town, South Africa	Trondheim, Norway	2021-10-03T12:01:00.000Z	2021-10-18T03:25:00.000Z
Mayport, USA	Anchorage, Alaska	2021-04-18T12:01:00.000Z	2021-05-15T06:31:00.000Z
San Diego, USA	Singapore	2021-04-04T12:01:00.000Z	2021-04-21T20:19:00.000Z
Busan, South Korea	Mayport, USA	2020-11-29T12:01:00.000Z	2020-12-28T08:25:00.000Z
Okinawa, Japan	San Diego, USA	2020-11-15T12:01:00.000Z	2020-11-28T01:01:00.000Z
Souda Bay, Greece	Naples, Italy	2020-11-15T12:01:00.000Z	2020-11-20T20:55:00.000Z

Origin	Destination	StartDtg	EndDtg
Bahrain	Sao Luis, Brazil	2020-10-27T12:01:00.000Z	2020-11-15T21:31:00.000Z
Manila, Philippines	Guam	2021-04-11T12:01:00.000Z	2021-04-18T13:01:00.000Z
Trondheim, Norway	San Diego, USA	2021-09-12T12:01:00.000Z	2021-10-09T09:07:00.000Z
Sydney, Australia	Mayport, USA	2021-04-18T12:01:00.000Z	2021-05-11T08:49:00.000Z
Busan, South Korea	San Antonio, Chile	2021-08-22T12:01:00.000Z	2021-09-10T08:37:00.000Z
Guam	Rota, Spain	2021-10-10T12:01:00.000Z	2021-11-08T02:13:00.000Z
San Diego, USA	Norfolk, USA	2021-09-19T12:01:00.000Z	2021-10-12T19:01:00.000Z
Pearl Harbor, USA	Souda Bay, Greece	2021-09-12T12:01:00.000Z	2021-10-10T01:43:00.000Z
Guam	Bahrain	2021-04-04T12:01:00.000Z	2021-04-25T06:07:00.000Z
Naples, Italy	Singapore	2020-10-04T12:01:00.000Z	2020-10-27T10:37:00.000Z
Sao Luis, Brazil	Naples, Italy	2020-10-04T12:01:00.000Z	2020-10-15T01:13:00.000Z
Pearl Harbor, USA	Sydney, Australia	2020-12-06T12:01:00.000Z	2020-12-18T00:07:00.000Z
Diego Garcia	Busan, South Korea	2020-12-20T12:01:00.000Z	2021-01-10T03:07:00.000Z
Pearl Harbor, USA	Rota, Spain	2020-12-20T12:01:00.000Z	2021-01-14T09:55:00.000Z
Diego Garcia	San Antonio, Chile	2020-11-29T12:01:00.000Z	2020-12-18T12:19:00.000Z
Trondheim, Norway	San Antonio, Chile	2020-10-04T12:01:00.000Z	2020-10-25T09:25:00.000Z
Cape Town, South Africa	San Diego, USA	2020-10-04T12:01:00.000Z	2020-10-23T20:13:00.000Z
San Antonio, Chile	Naples, Italy	2021-04-04T12:01:00.000Z	2021-04-24T04:49:00.000Z
Diego Garcia	Cape Town, South Africa	2021-09-12T12:01:00.000Z	2021-09-23T11:49:00.000Z
Pearl Harbor, USA	Mayport, USA	2021-09-19T12:01:00.000Z	2021-10-13T03:01:00.000Z
Guam	Diego Garcia	2021-10-10T12:01:00.000Z	2021-10-28T15:43:00.000Z
Manila, Philippines	Anchorage, Alaska	2020-10-27T12:01:00.000Z	2020-11-09T14:31:00.000Z
Okinawa, Japan	Busan, South Korea	2020-12-06T12:01:00.000Z	2020-12-11T09:19:00.000Z
Bahrain	Busan, South Korea	2020-10-18T12:01:00.000Z	2020-11-10T19:07:00.000Z

Origin	Destination	StartDtg	EndDtg
Souda Bay, Greece	Norfolk, USA	2020-12-13T12:01:00.000Z	2020-12-24T17:07:00.000Z
Busan, South Korea	Souda Bay, Greece	2021-08-22T12:01:00.000Z	2021-09-24T05:43:00.000Z
Trondheim, Norway	Souda Bay, Greece	2021-08-15T12:01:00.000Z	2021-08-25T00:37:00.000Z
Anchorage, Alaska	Pearl Harbor, USA	2021-08-22T12:01:00.000Z	2021-08-30T05:19:00.000Z
Singapore	Trondheim, Norway	2021-04-18T12:01:00.000Z	2021-05-11T17:43:00.000Z
Mayport, USA	Manila, Philippines	2021-04-04T12:01:00.000Z	2021-05-04T19:13:00.000Z
San Diego, USA	Guam	2021-04-25T12:01:00.000Z	2021-05-07T12:01:00.000Z
Naples, Italy	Guam	2021-10-03T12:01:00.000Z	2021-11-03T00:31:00.000Z
Sao Luis, Brazil	Diego Garcia	2021-10-03T12:01:00.000Z	2021-10-20T07:19:00.000Z
Guam	Trondheim, Norway	2020-12-20T12:01:00.000Z	2021-01-04T08:13:00.000Z
San Diego, USA	Sao Luis, Brazil	2020-10-18T12:01:00.000Z	2020-11-07T17:49:00.000Z
Mayport, USA	Pearl Harbor, USA	2020-10-11T12:01:00.000Z	2020-11-04T03:01:00.000Z
San Antonio, Chile	San Diego, USA	2020-09-27T12:01:00.000Z	2020-10-08T16:43:00.000Z
Rota, Spain	Sydney, Australia	2021-09-05T12:01:00.000Z	2021-09-28T12:25:00.000Z
Norfolk, USA	Singapore	2021-04-18T12:01:00.000Z	2021-05-10T06:01:00.000Z
Souda Bay, Greece	Singapore	2021-09-12T12:01:00.000Z	2021-10-06T04:19:00.000Z
Bahrain	Okinawa, Japan	2021-04-11T12:01:00.000Z	2021-05-03T22:19:00.000Z
Singapore	Bahrain	2020-11-01T12:01:00.000Z	2020-11-12T19:55:00.000Z
Naples, Italy	Bahrain	2020-11-15T12:01:00.000Z	2020-12-09T05:31:00.000Z
Sydney, Australia	Mayport, USA	2020-11-15T12:01:00.000Z	2020-12-08T08:49:00.000Z
Busan, South Korea	Naples, Italy	2020-12-06T12:01:00.000Z	2021-01-07T12:13:00.000Z
Rota, Spain	Norfolk, USA	2021-10-10T12:01:00.000Z	2021-10-19T05:37:00.000Z
San Antonio, Chile	Manila, Philippines	2021-09-19T12:01:00.000Z	2021-10-09T16:13:00.000Z
San Antonio, Chile	Bahrain	2020-11-29T12:01:00.000Z	2020-12-21T02:43:00.000Z

Origin	Destination	StartDtg	EndDtg
San Diego, USA	Bahrain	2020-12-20T12:01:00.000Z	2021-01-13T14:37:00.000Z
Naples, Italy	Trondheim, Norway	2020-10-04T12:01:00.000Z	2020-10-13T06:49:00.000Z
Cape Town, South Africa	Singapore	2020-10-04T12:01:00.000Z	2020-10-17T16:19:00.000Z
Mayport, USA	Singapore	2021-09-12T12:01:00.000Z	2021-10-04T06:01:00.000Z
Diego Garcia	Sydney, Australia	2021-04-04T12:01:00.000Z	2021-04-17T02:13:00.000Z
Anchorage, Alaska	Diego Garcia	2021-04-11T12:01:00.000Z	2021-05-05T09:07:00.000Z
Busan, South Korea	Mayport, USA	2021-09-12T12:01:00.000Z	2021-10-11T08:25:00.000Z
Busan, South Korea	Cape Town, South Africa	2020-12-06T12:01:00.000Z	2020-12-30T06:19:00.000Z
Norfolk, USA	Naples, Italy	2020-11-01T12:01:00.000Z	2020-11-11T18:01:00.000Z
Souda Bay, Greece	San Diego, USA	2020-12-06T12:01:00.000Z	2021-01-03T07:13:00.000Z
Souda Bay, Greece	San Antonio, Chile	2020-11-15T12:01:00.000Z	2020-12-06T15:07:00.000Z
Pearl Harbor, USA	San Antonio, Chile	2021-08-15T12:01:00.000Z	2021-08-27T18:55:00.000Z
Trondheim, Norway	Pearl Harbor, USA	2021-09-05T12:01:00.000Z	2021-10-02T17:13:00.000Z
Manila, Philippines	Okinawa, Japan	2020-09-27T12:01:00.000Z	2020-10-03T12:31:00.000Z
Guam	Rota, Spain	2020-10-11T12:01:00.000Z	2020-11-09T02:13:00.000Z
Guam	Souda Bay, Greece	2021-04-25T12:01:00.000Z	2021-05-26T18:01:00.000Z
Diego Garcia	Souda Bay, Greece	2021-04-04T12:01:00.000Z	2021-04-26T08:43:00.000Z
Trondheim, Norway	Naples, Italy	2021-10-03T12:01:00.000Z	2021-10-12T06:49:00.000Z
Sao Luis, Brazil	Busan, South Korea	2021-10-03T12:01:00.000Z	2021-10-28T20:55:00.000Z
Pearl Harbor, USA	Busan, South Korea	2020-10-18T12:01:00.000Z	2020-10-29T00:49:00.000Z
San Diego, USA	Anchorage, Alaska	2020-12-20T12:01:00.000Z	2020-12-27T23:37:00.000Z
Sydney, Australia	San Diego, USA	2020-12-13T12:01:00.000Z	2020-12-26T22:01:00.000Z
Singapore	Pearl Harbor, USA	2020-10-18T12:01:00.000Z	2020-11-01T07:13:00.000Z
Singapore	Sao Luis, Brazil	2021-04-18T12:01:00.000Z	2021-05-06T21:25:00.000Z

Origin	Destination	StartDtg	EndDtg
Okinawa, Japan	Trondheim, Norway	2021-08-22T12:01:00.000Z	2021-09-05T18:19:00.000Z
Bahrain	Diego Garcia	2021-04-18T12:01:00.000Z	2021-04-25T04:13:00.000Z
Bahrain	Guam	2021-08-22T12:01:00.000Z	2021-09-12T06:07:00.000Z
Mayport, USA	Guam	2020-11-15T12:01:00.000Z	2020-12-12T20:07:00.000Z
Naples, Italy	Mayport, USA	2020-10-27T12:01:00.000Z	2020-11-07T15:01:00.000Z

LIST OF REFERENCES

- Barton N, Metzger EJ, Reynolds CA, Ruston B, Rowley C, Ole MS, Phelps M (2021) The Navy's Earth System Prediction Capability: a new global coupled atmosphere-ocean-sea ice prediction system designed for daily to subseasonal forecasting. *Earth and Space Science* 8(4), <https://doi.org/10.1029/2020EA001199>.
- Chu PC, Miller SE, Hansen JA (2014) Fuel-saving ship route using the Navy's ensemble meteorological and oceanic Forecasts. *Journal of Defense Modeling and Simulation* 12(1): 41–56, DOI: 10.1177/1548512913516552
- Copernicus Climate Change Service, Climate Data Store (2023) ERA5 hourly data on single levels from 1940 to present. Accessed May 26, 2023, <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview>.
- Grifoll M, Borén C, Castells-Sanabra M (2022) A comprehensive ship weather routing system using CMEMS products and A* algorithm. *Ocean Engineering* 255, <https://doi.org/10.1016/j.oceaneng.2022.111427>.
- Hall SL (2012) Effect of the environment and environmental uncertainty on ship routes. Master's thesis, Naval Postgraduate School, Monterey, CA, Defense Technical Information Center (ADA 562795)
- Hogan TF, Liu M, Ridout JA, Peng MS, Whitcomb TR, Ruston BC, Reynolds CA, Eckermann SD, Moskaitis JR, Baker NL, McCormack JP, Viner KC, McClay JG, Flatau MK, Xu L, Chen C, Chang SW (2014) The Navy global environmental model. *Oceanography* 27(3):116–25, <http://www.jstor.org/stable/24862194>.
- HYCOM (2023) About Us. Accessed April 15, 2023, <https://www.hycom.org/about>.
- Jacques R (2023) Ship route construction techniques used by the U.S. Navy provided to author via personal communication, March 31.
- Lantz SW (2014) Incorporation of tropical cyclone avoidance into automated ship scheduling. Master's Thesis, Naval Postgraduate School, Monterey, CA, Defense Technical Information Center (ADA 607722).
- MacCalman AD (2013) Flexible space-filling designs for complex system simulations. Doctoral dissertation, Naval Postgraduate School, Monterey, CA, Defense Technical Information Center (ADA 585718).

- Miller SE (2012) Smart voyage planning model sensitivity analysis using ocean and atmospheric models including ensemble methods. Master's Thesis, Naval Postgraduate School, Monterey, CA, Defense Technical Information Center (ADA 567352).
- National Transportation Safety Board (2017) Sinking of the U.S. cargo vessel El Faro. Marine Accident Report NTSB/MAR-17/01, <https://www.nts.gov/investigations/AccidentReports/Reports/SPC1801.pdf>.
- National Weather Service (2023) WaveWatch III Development. Accessed April 11, 2023, https://www.weather.gov/sti/coastalact_ww3#:~:text=The%20core%20of%20the%20framework,equation%20for%20wavenumber%2Ddirection%20spectra.
- Naval Vessel Register (2023) Fleet Size. Accessed January 7, 2023, <https://www.nvr.navy.mil/NVRSHIPS/FLEETSIZE.HTML>.
- Office of the Under Secretary of Defense for Acquisition and Sustainment (2021) Fiscal Year 2020 Operational Energy Annual Report. <https://www.acq.osd.mil/eie/Downloads/OE/FY20%20OE%20Annual%20Report.pdf>.
- Pueschel S (2017) Optimization of an advanced multi-junction solar-cell design for space environments (AM0) using nearly orthogonal latin hypercubes. Master's Thesis, Naval Postgraduate School, Monterey, CA, Defense Technical Information Center (AD 1046507).
- Sanchez PJ (2021) Datafarming (version 1.4.0): RubyGem. <https://rubygems.org/gems/datafarming>.
- Sanchez SM, Lucas TW, Sanchez PJ, Nannini CJ, Wan H (2012) Designs for large-scale simulation experiments, with applications to defense and homeland security. *Hinkelmann and Kempthorn* 3(12): 413–441, <https://hdl.handle.net/10945/35261>.
- Sanchez SM, Wan H (2012) Work smarter, not harder: a tutorial on designing and conducting simulation experiments. *Proceedings of the 2012 Winter Simulation Conference* (Berlin, Germany), <https://core.ac.uk/download/pdf/36737012.pdf>.
- Sanchez SM., Sanchez PJ (2017) Better big data via data farming experiments. *Advances in Modeling and Simulation* 159–179, https://doi.org/10.1007/978-3-319-64182-9_9.
- Sidoti D (2023a) Information about STARS algorithm provided to author via personal communication, March 29.
- Sidoti D (2023b) Information regarding ship datasets for TMPLAR provided to author via personal communication, January 20.

Sidoti D (2023c) Information regarding TMPLAR calculations for fuel consumption provided to author via personal communication, February 2.

Sidoti D, Avvari GV, Mishra M, Zhang L, Nadella BK, Peak JE, Hansen JA, Pattipati KR (2016) A multiobjective path-planning algorithm with time windows for asset routing in a dynamic weather-impacted environment. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 47(12), 10.1109/TSMC.2016.2573271.

United States Naval Academy (2023) Ocean and atmospheric sciences. Accessed April 12, 2023, <https://www.usna.edu/Oceanography/ProspectiveStudents/Military-Applications.php>.

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