Master's degree thesis

LOG950 Logistics

Evaluation of supply vessel schedules robustness with a posteriori improvements

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Preface

This thesis is submitted in fulfillment of the degree requirement for Master of Science (MSc) in Industrial Logistics at Molde University College – Specialized University in Logistics, Molde, Norway. The work described in the thesis was performed during the time interval from November 2013 to May 2014 with professor Irina Gribkovskaia from Molde University College – Specialized University in Logistics as the main supervisor. Ellen Karoline Norlund a PhD student supervised by Irina Gribkovskaia and a Senior Consultant At the Department of Logistics and Emergency Response at Statoil in collaboration with Irina and me formulated the problem for this research. Ellen also provided me with weather data observations collected at the Norwegian continental shelf zone and supply vessel schedules used in Statoil to be evaluated and compared in practical part of this thesis. Additionally, professor Jaume Barcelo from the Technical University of Catalonia, Barcelona, Spain, and associate professor Vladimir Malugin from the Belarusian State University, Minsk, Belarus, have been research co-advisors at various stages of this work.

The subject of this thesis is the development of advanced analytical methods for efficient evaluation of supply vessel schedules with a posteriori improvements. Several research problems arose in this perspective and choice for their solution method was always dictated by the core of each particular problem. The thesis consists of a brief introduction to the research area, followed by the chapters dedicated to problem statement, methodology review, data analysis, simulation tool development and finally schedules' evaluation. The last 3 chapters provide some valuable scientific contribution in forms of models, algorithms and analysis.

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First and foremost I would like to gratitude my supervisor Irina Gribkovskaia for her most active involvement in my work. This master thesis got quite some benefits from her constructive advices and comments.

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The last but not least is to mention that I cannot even express my gratitude and affection to my family and friends. Sometimes even without realizing that you all supported and inspired me very much. Mentioning all of you would make the list far too long, but each and every of you is indeed dear to me in your own special way.

Molde, Norway Aliaksandr Hubin
May, 2014

Abstract

Offshore installations need supply vessel services on a regular basis. Weather uncertainty impacts on how service is performed. Different robustness and speed optimization strategies are generally incorporated into construction of supply vessel weekly plans. To compare performance of these strategies by evaluating robustness of generated schedules with different service parameters a discrete-event simulation model is developed. Based on results from simulation, strategies for improving robustness incorporated into the simulation model are applied to modify the schedules.

Key Words: OFFSHORE UPSTREAM LOGISTICS, SUPPLY VESSEL OPERATIONS, STATISTICAL DATA ANALYSIS, ARIMA SIMULATION, DISCRETE EVENT SIMULATION, SHIP ROUTING AND SCHEDULING, ROBUSTNESS EVALUATION, MULTICRITERIA RANKING, A POSTERIORI IMPROVEMENTS.

Contents

1. Introduction

Oil and gas industry has become one of the most developed branches of Norwegian economy during the last decades, which resulted in a particularly large share of GDP and GNP of the country created in it. Cost efficient activities in oil and gas industry might well lead to quite large savings and thus increase of national GDP/GNP. At the production stage in oil and gas supply chain a lot of costs are associated with offshore logistics. Installations have high and urgent requests on equipment and materials (the production might even stop when they are not met) and limited storage capacities. Thus, necessary resources must be delivered from supply bases to offshore installations by supply vessels on time as well as used materials and waste must be brought back on shore. These operations form one of the most costly parts of offshore upstream logistics. A daily cost of hiring and using a supply vessel reaches hundreds of thousands of NOK. Thus, organizing supply vessel operations in an efficient way might well result in sufficiently large savings for a company.

Supply vessel planning on tactical level implies construction of weekly sailing plans valid for a certain time period. A weekly plan includes sailing plans for all vessels during the week, which in turn represent for each vessel a set of consecutive voyages.

Supply vessel planning problem (SVPP) addressed for construction of weekly sailing plans has been studied by different researchers. In particular, Halvorsen-Weare et al. (2012), Shyshou et al. (2012), Shyshou (2010) addressed SVPP for Statoil case. They studied fleet composition and construction of weekly sailing plans for deterministic environment and also provided different algorithms for single- and multi-base cases, which can be used for building weekly supply vessel schedules. Norlund and Gribkovskaia (2013) addressed the problem of building these schedules in an environmentally friendly way by means of applying sailing speed optimization techniques.

Ideally these weekly sailing plans should be constructed with an objective to meet installations' requests in a cost efficient and environmentally friendly way, taking into account different sorts of uncertainty. One of the major sorts of uncertainties that appear in supply vessel planning is weather stochasticity: for example, wave directions and wave heights significantly decrease planned sailing speeds and increase service time at installations. Moreover according to the rules and regulations these services must be stopped when wave height reaches a certain point (4.5 and more meters). Construction of robust weekly sailing plans by means of the simulation tool was addressed by Halvorsen-Weare and Fagerholt (2011).

Weather uncertainty was also addressed by other researchers. Shyshou et al. (2010) carried out a simulation study of fleet sizing problem arising in offshore anchor handling operations; he implemented weather uncertainty by means of probability distributions of significant wave heights. Another paper concerning a relevant problem was published by Maisiuk and Gribkovskaia (2013) who present a discrete-event simulation model that evaluates alternative fleet size configurations for supply vessels on the annual time horizon.

Weather uncertainty, however, provokes not only the necessity to carry out robust supply vessel planning, but also to evaluate robustness of the constructed schedules. Emissions of greenhouse gases, which are desired to be low, linearly depend on fuel consumptions, thus the last parameter is also a matter of a particular interest. In this thesis we develop a tool for schedule evaluation in terms of robustness versus fuel consumption", which takes into consideration weather conditions by means of event based simulation. Moreover, we incorporate into this tool some options for a posteriori modifications of weekly sailing plans (which we define in this thesis as schedules) so as to improve their quality with a trade-off between robustness and fuel consumption.

Conduction of such research represents a rather challenging task as it provokes four quite large and sophisticated sub problems to be resolved. First, substantial and advanced statistical data analysis of weather data has to be carried out. The challenge is that time series of weather parameters are long lasting observations of auto correlated and correlated between each other data series collected at the Norwegian continental shelf zone every 3 hours for more than 50 years; moreover these time series are both non-stationary and heteroscedastic, which creates and additional challenge for modelling them properly. At second, development of a simulation model of supply vessel plans itself is a hard task as it needs combining such things as weather simulation, business logics understanding, routing and discrete event simulation into a single compact model. A posteriori improvements of supply vessel sailing plans have not been studied much yet, thus their choice and implementation is a difficult issue to be resolved. And finally evaluation of schedules is indeed a challenge, since it has to be decided which parameters have to be chosen and why, how to estimate them and finally how to aggregate them in order to get a multicriteria-scaled measure.

The title for this thesis is formulated as "Evaluation of supply vessel schedules robustness with a posteriori improvements". Such research is indeed relevant since not so much studies of this kind have yet been done, whilst the problem is rather relevant for real oil companies; moreover the developed tool brings particular managerial contribution for oil companies that operate offshore.

2. Problem statement

As we have already mentioned, supply vessel planning on tactical level implies construction of circular weekly vessel sailing plans valid for a certain time period. As it can be seen on example in Figure B-1 in the appendix of this thesis, this plan consists of individual schedules for all vessels, which in turn are represented by sequences of voyages built to satisfy installations' requests and characterized by the assigned scheduled arrival, discharge and departure times. Voyages consist of visits to installations and a supply base. A connection and corresponding to it sailing between any pair of locations we will understand as a *leg*.

The process of constructing and afterwards performing of these vessel sailing plans is additionally complicated by a number of factors, such as presence of working hours at the installations and the base, limitations on voyage durations (they are usually up to 2 or 3 days in practice), necessity to provide a spread of visits to installations, departures from the supply base to installations, limited capacities of a supply base and installations.

Moreover whilst constructing these sailing plans, weather uncertainty, which influence both sailing and service durations, should be taken into account; the last is currently done by means of having slacks for voyages incorporated into their durations. However, adding inaccurate slacks to durations of voyages might either lead to increase of idle time of vessels, in case slacks are too large or lead to lowered service level in case these slacks are smaller than needed. Moreover adding slacks only to the beginning or end of a voyage might still remain actual the problem of not fitting of working hours at the installations and the supply base as a result of weather uncertainty, which in turn means that it could be beneficial to add smaller slacks to each leg of the voyage and thus assign in a more accurate way arrival, discharge and departure time of vessels at installations and supply bases so as to achieve a better level of utilization of robust schedules. This means a proper statistical analysis of voyage durations and/or durations of legs of this voyage taking weather uncertainty into account. This is also important for building balanced schedules with respect to weather changes. Supply vessel sailing plans based on a proper combination of robust voyages satisfying all of the relevant constraints are considered as robust.

Taking all above constraints into consideration for construction of plans is an extremely difficult task, that is why different sorts of assumptions and simplifications are made. These assumptions might (or might not) influence execution of weekly sailing plans in reality. The problem addressed in this work is to develop a tool able to simulate weekly sailing plans for typical winter and summer periods, evaluate their performance and suggest a posteriori improvements of weekly sailing plans.

Starting from the following section of this thesis we will use a simple term *schedule* meaning by that a *vessel sailing plan* (see the definitions in the ongoing section).

2.1 General definitions

In what follows the next definitions will be used:

Offshore Installation (oil platform, offshore platform, oil rig or just installation) is a large construction located off the shore, which has the facilities to drill wells, extract and process oil and natural gas, and temporarily store product until it can be brought to the shore for refining and marketing. They also might have limited working hours (time windows).

Service Request for an Offshore Installation is a number of visits to the installation within a time horizon (week) in order to satisfy its demand.

Supply Vessel (PSV, vessel) is a vehicle (ship) designed for servicing offshore oil installations. They range from 20 to 100 meters in length and accomplish a variety of tasks, among which the primary task is transportation of cargo, goods and/or personnel to and from offshore oil installations and other offshore structures.

Voyage of a Vessel is an ordered set of visits to offshore installations starting and ending at a supply base mapped by a set {location, times (arrival, discharge, departure)}.

Vessel Weekly Schedule is a set of consecutive voyages assigned to a vessel to be completed on a weekly time horizon.

Weekly supply vessels sailing plan is a set of vessels' weekly schedules.

Schedule (supply vessels plan in general) is an ordered set of visits to offshore installations and supply bases mapped by a set {location, times (arrival, discharge, departure), vessel} during a given time horizon.

Significant Wave Height (SWH) is the mean wave height (trough to crest) of the highest third of the waves.

Wave Direction (WD) is the direction from where the wave originates in either cardinal directions or in azimuth degrees.

We also introduce the following definitions:

Evaluate a Schedule means to estimate a set of key robustness factors (parameters) like service level, average tardiness, maximal tardiness of an individual installation, average deviation from scheduled times, fuel costs etc., and their aggregated measure in order to address quality of a schedule in terms of robustness versus fuel consumption.

Weather Uncertainty (for the addressed case) is stochasticity induced by changes of wave directions and significant wave heights over time. Weather uncertainty, thus, consists of two components: wave height uncertainty and wave direction uncertainty. These factors lead to lengthening of voyages, inability to perform planned visits at estimated time and etc.

A Posteriori Improvement of a Schedule is a set of modifications of a schedule being evaluated (e.g. utilization of slacks between voyages, rerouting of voyages, swapping voyages between vessels and etc.) so as to improve its quality in terms of robustness versus fuel consumption.

2.2 Problems and objectives of the research

Thus, with respect to problem definition above the research **problem** is divided into the following set of sub problems to be resolved:

✓ Formulation and substantiation of criteria for evaluation of schedule robustness
✓ Statistical data analysis for weather modelling
✓ Development and implementation of a simulation model for schedules' evaluation
✓ Evaluation of given schedules with respect to a set of chosen criteria
✓ Development and implementation of an integrated simulation-optimization tool for a posteriori schedules' improvement

Basing on the issues and problems stated above, we can formulate **objectives** of the research:

1. Generate weather data by means of estimating the parameters of the appropriate stochastic processes and/or distributions and clustering weather conditions according to some parameters and simulation of them. Note that there are two types of weather uncertainty:

a. *Wave height uncertainty,* its geographical and seasonal clustering and impact on vessel speed and sailing duration times. SWH might be considered by means of stochastic processes and/or probability distributions of wave height.

b. *Wave direction uncertainty,* its geographical and seasonal clustering and impact on vessel speed and sailing duration times. WD might be considered by means of stochastic processes and/or probability distributions of wave direction.

2. Build an event based simulation model for emulating supply vessel schedules having the modeled weather incorporated.

3. Suggest key parameters for evaluation of quality of schedules. Possible service parameters:

   a. Service level for the whole schedule;
   b. Service level for any subset of installations from the schedule;
   c. Service level for the voyages of vessels;
   d. Tardiness of arrival, discharge and departure times of the whole schedule;
   e. Deviations of arrival, discharge and departure times from those scheduled;
   f. Number of missed visits;
   g. Number of not performed voyages;
   h. Number of not performed weekly schedules;
   i. Fuel consumptions and fuel costs;

4. Suggest and substantiate an aggregation criterion and/or ranking criterion based on the key parameters above in order to have an aggregated evaluation measure for the schedules.

5. Evaluate robustness of schedules.

6. Suggest and implement approaches for improvements of the given schedules (a posteriori). Possible ways to do that are listed below:

   a. By means of utilizing slacks between voyages;
   b. By means of swapping voyages between the vessels;
   c. By means of speed adjustments with respect to the forecasted weather;
   d. By means of a combination of the improvements above.

2.3 Data sources

Primary Data

It seems to be quite obvious that in the very case of our research not so many sources of primary data will most likely be used. However among them the following types of data and sources might be highlighted:

1. Information about:

- what are the main restrictions, limitations and constraints for weekly vessel schedules to be taken into account;
- technical rules for service;
- supply base policy for supply vessel departures;

2. Expert estimates analysis for:

- service times distributions at the installations and/or supply bases;
- changes of service time at the installation with respect to weather;

Secondary Data

It seems to be rather clear that most of the data used in this kind of research should be secondary data, provided by real oil companies, weather institutions and etc. Ideally such data as those represented below is needed for successful research:

1. Vessel configurations:
    - sizes and capacities;
    - economic speed and speed limits;
    - deadweights;
    - fuel consumptions;
    - fuel costs;
    - emissions of greenhouse gases.
2. Supply bases configuration:
    - service times for each vessel;
    - opening and closing hours;
    - geographical locations.
3. Installations data
    - set of installations and their geographical positions;
    - working hours;

- requests;
- service durations.

4. Weather data
    - time series for significant wave heights on a given grid of points;
    - time series for wave directions on a given grid of points;

It is quite clear that getting all these data might well be a very difficult job. Hence, once the situation is thoroughly studied, relevant models built; these models will be first tested on small samples of modeled data. Once models prove to be working well on modeled data, real world data should be addressed; in case the samples are not large enough statistical data analysis and/or simulation may be addressed to generate additional inputs. In case some data is impossible to get either models should be adjusted or modeled data should be used to make relevant stubs.

3. Methodology and literature review

3.1 Solutions techniques

A number of different operation research based techniques are applied in this master thesis. In this section we mention some of them and describe the way they are applied. The more detailed description of them is provided in the dedicated to them chapters of this thesis.

Time series modeling

According to Box et al. (1976), time series analysis comprises methods for analyzing time series data so as to extract meaningful statistics and other characteristics of the data. Forecasting models are used to predict future values based on previously observed values, whilst regression analysis is often employed in such a way as to test theories that current values of one or more independent time series affect a current value of another time series.

Significant wave heights as well as wave directions are auto correlated time series (which are moreover correlated with one another between different geographical points) thus for weather modeling different sorts of stochastic processes should be addressed (ARIMA, VAR, N-Markov chains, etc.) with respect to geographical and/or seasonal weather clusters. This means, we have to find the most relevant approach for modeling of weather at the Norwegian continental shelf and the area around installations of interest.

Discrete event based simulation

According to Robinson (2004) discrete event based simulation models are used to model the operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change in the system is assumed to occur; thus the simulation can directly jump in time from one event to the next.

This approach is used for simulation of vessel schedules (including sailing, waiting and servicing of the installations) with respect to modeled weather.

Agent based simulation

Agent based simulation is a class of computational models for simulating actions and interactions of autonomous and their influence on the system as a whole (Niazi et al. 2011).

This methodology occurs when deciding about changes in the sequence of visits within a voyage during sailing or when swapping voyages between the vessels (when for instance one of them is late from the previous route, whereas another one (with the same parameters) is waiting for its departure at the supply base area) or when doing any kinds of dynamic speed adjustments.

Combinatorial optimization

Combinatorial optimization is a topic that consists of finding an optimal object from a finite set of objects (Schrijver 2006).

Combinatorial optimization problems could be addressed during the simulation itself for implementing agent based behavior and attempting to do a posteriori optimization of the schedules (rerouting and rescheduling in particular).

Expert assessment theory

Expert evaluation (expert assessment) is the procedure of obtaining system estimates based on the opinions of experts (experts) in order to make the subsequent decision (choice).

This approach should be addressed when estimating distributions of service times at the installations and the supply base, since there are hardly likely any sources of secondary data for that sort of statistics. This approach might as well be addressed when scaling multicriteria decisions.

Threshold aggregation and/or multicriteria ranking

Threshold aggregation is an aggregation procedure based on some threshold rule for construction of an output ranking from individual m-graded rankings with an arbitrary integer $m \geq 2$ (Aleskerov et al. 2010).

Another approach is to use multicriteria ranking algorithms described by Zopoundis and Doumpos (2002), like TOPSIS, ELECTRE, UTADIS, etc. These approaches use some distance and/or preference measure to rank alternatives with respect to a number of criteria.

Both of these techniques might be addressed at the stage of building an aggregation criterion for key parameters so as to have an aggregated measure of schedules in terms of robustness versus fuel consumption.

3.2 Literature review

In this section we carry out additional review of the literature on the chosen methodology applied to similar problems so as to get a better idea of what to pay especial attention to during our research.

3.2.1 Weather modelling

As it has already been mentioned a very important part of the research is dedicated to weather modeling and forecasting and in particular to analysis of wave heights and wave directions components of weather in the Norwegian offshore zone, where the installations of interest are located. Two groups of studies concerning weather modelling are addressed: those based on statistical distribution analysis and those based on stochastic processes analysis.

Caires and Sterl (2004) present in their article global estimates of long term return values of wind speed and significant wave heights. These estimates are based on data; they also are linearly corrected using estimates based on buoy data. Calculation of return values in their research is based on the peak solver-threshold method. Large amounts of data used in this study provide evidence that the distributions of significant wave height and wind speed data could belong to the family of exponential distributions. Further, the effect of space and time variability of SWH and WS (wind speed) on the prediction of their edge values is addressed. Thus research in this article might well help us model statistical distributions of significant wave heights in the Norwegian continental shelf as well as carry out clustering with respect to both seasons and geographical locations of the installations and routes among them with respect to these distributions. Another detailed example of statistical analysis of waves is presented by Bauer and Staabs (1998). Comparison of different models for wave heights is carried out in this paper. Forristall (2012) presents the paper, studying how well the

Rayleigh distribution matches the observed distribution of wave heights. It is claimed that most of the controversy stems from comparisons are based on different definitions of the significant wave height. Once consistent definitions are used, all available data support the conclusion that the Rayleigh distribution over-predicts the heights of the higher waves in a record. Analysis of 116 hours of hurricane-generated waves in the Gulf of Mexico permitted the empirical fitting of the data to a Weibull distribution. Another paper by Nerzic and Prevosto (1998) describes a model for estimation of maximal wave heights in a given sea state. Authors modify standard Weibull and Rayleigh distributions using a third order Stokes expansion of the so called wave envelope. What is especially important, authors conclude that the suggested approach have been tested on real data in the North Sea and provided much better predictions than standard models. Moreover the proposed model is relatively easy to apply and, thus, could be an effective tool in determining extreme wave and crest heights for offshore structure design purposes.

A particularly important for our case research considering wave heights time series is described by Guedes Soares and Cunha (2000) who generalize the application of univariate models of the long-term time series of significant wave height to the case of the bivariate series of significant wave height and mean period. A brief review of the basic features of multivariate autoregressive models is presented, and then applications are made to the wave time series of Figueira da Foz, in Portugal. It is demonstrated that the simulated series from these models exhibit the correlation between the two parameters, a feature that univariate series cannot reproduce. An application to two series of significant wave height from two neighboring stations shows the applicability of this type of models to other type of correlated data sets. This is exactly the case of our research since we have a set of correlated between each other auto correlated time series of significant wave heights and wave directions. A neural networks approach for improving the quality of prediction of significant wave heights is suggested by Makarynskyy (2003); this approach might well be used in our case as well when simulating the prediction of wave heights during the voyage.

However it should be mentioned that none of the papers described above considers the Markov stochastic processes for wave height modeling and/or prediction, which are addressed by Halvorsen-Weare and Fagerholt (2011), which makes it necessary to do additional and probably more advanced research for finding the most appropriate model for modeling stochastic processes of significant wave heights and wave directions at the Norwegian continental shelf.

3.2.2 Event based and agent based simulation

Another subject of interest for us regarding event based simulation might be the paper by Goldsman et al. (2002) discussing the issues concerning the simulation of transportation systems. In particular, a number of implementation tricks that are designed to make the modeling and coding processes more efficient and transparent are demonstrated in that paper. Authors also present examples involving the simulation of commercial airline and military sealift operations. Even though the article has a different from ours scope, it might still be useful due to the implementation tricks concerning modelling and coding described.

Yet another aspect of simulation that will be applied in our research may be agent based behavior of the entities (in order to carry out a posteriori optimization of the schedules of supply vessels). This approach should also be studied in the appropriate literature. For instance, Arentze and Timmermans (2002) describe the conceptual development, operationalization and empirical testing of a Learning-based Transportation Oriented Simulation System. This activity-based model of activity-travel behavior is derived from theories of choice heuristics that consumers apply when making decisions in complex environments. The model, one of the most comprehensive of its kind, predicts which activities are conducted and decides for such factors as when, where, for how long, with whom, and chooses the transport mode involved. In addition, various situational, temporal, spatial, spatial-temporal and institutional constraints are incorporated in their model. Another paper concerning agent based behavior in transportation was presented by Wahle et al. (2002). This group of researchers studies the impact of real-time information in a two-route scenario using agent-based simulation. In particular, they address a basic two-route scenario with different types of information and study the impact of it using simulations. The road users are modeled as agents, which is a natural and promising approach to describe them. Different ways of generating current information are tested.

4. Data analysis of weather parameters

Time series analysis and modeling for significant wave height and wave direction at offshore locations has quite some applications in engineering, scheduling of vessels and organizing of other sorts of offshore operations. It is a useful complement to the models based on statistical distributions of the corresponding parameters which characterize weather in different areas. Whereas the distribution-based models provide probabilities of occurrence of independent events at random points in time, time series-based models also take into consideration autocorrelation between the consecutive events and provide researchers with an opportunity to build a close to reality model based on the corresponding discrete and/or continuous time-based stochastic processes.

4.1 Methods for constructing point estimates and their properties

By definition **a sample** of size n $X = \{x_1 ... x_n\}$ – is a set of n observations over ξ, received from an experiment.

By definition **an estimator** $\hat{A}$ – is some statistics $\hat{A} = \hat{A}(X) : R^{n\times N} \to R^K$ used to estimate unknown parameters.

Estimator $\hat{A}$ might have the following **properties:**

- ✓ $\hat{A}$ is Consistent if $\hat{A} \xrightarrow[n\longrightarrow\infty]{P} A, \forall A$;
- ✓ $\hat{A}$ is Strongly Consistent if $\hat{A} \xrightarrow[n\longrightarrow\infty]{a.s.} A, \forall A$;
- ✓ $\hat{A}$ is Unbiased if $E_A\{\hat{A}\} = A, \forall n \geq 1$;
- ✓ $\hat{A}$ is Asymptotically Unbiased if $E_A\{\hat{A} - A\} \xrightarrow[n\longrightarrow\infty]{} 0$;
- ✓ $\hat{A}$ is Efficient if it is Unbiased and $\hat{A} = \arg\min\limits_{A}\left(V\{A\}\right)$,

  where $V\{\hat{A}\} = E_A\{(\hat{A} - A)(\hat{A} - A)^T\}$ is a covariance matrix of $\hat{A}$;
- ✓ $\hat{A}$ is Asymptotically Normal if $\sqrt{n}(\hat{A} - A) \xrightarrow{d} N_n(0, V)$;
- ✓ $\hat{A}$ is Asymptotically Efficient if its asymptotical covariance matrix is a lower bound of covariance for all consistent asymptotically normal estimators.

Further some most widely used methods for constructing estimators are presented.

Method of Moments (MM)

Let $X=(x_1,...,x_n)$ be a random sample from a distribution with some parametric CDF $F(x;\theta^0), x\in R^1, \theta^0=(\theta_1^0,...,\theta_m^0)$, where $\theta^0=(\theta_1^0,...,\theta_m^0)$ are unknown parameters to be estimated. Let $\forall k=\overline{1,m}$ $\exists$ a raw moment of order k:

$$\nu_k=\nu_k(\theta)=\int_{R^1} x^k dF(x;\theta). \qquad (4.1.1)$$

Then for real θ^0 we can find the corresponding moments $v_k^0=v_k(\theta^0)$ $k=\overline{1,m}$. On the other hands these moments might be numerically estimated:

$$a_k=\frac{1}{n}\sum_{t=1}^{n} x_t^k, \qquad (4.1.2)$$

where α_k is a strongly consistent estimator, in other words: $a_k \xrightarrow[n\to\infty]{п.н.} v_k^0$. Then the system of equations (4.1.3) might be constructed.

$$\begin{cases}\nu_1(\theta_1,...,\theta_m)=\alpha_1\\ \text{....................}\\ \nu_m(\theta_1,...,\theta_m)=\alpha_m\end{cases}, \qquad (4.1.3)$$

By solving such a system (exactly or numerically) $\widehat{\theta^0}=\left(\widehat{\theta_1^0},...,\widehat{\theta_m^0}\right)$ – a strongly consisted estimator based on the method of moments, is found.

Properties of MM estimator**:**

- Consistency
- Might be biased
- Simplicity

Maximal Likelihood Method

Let $X=(x_1,...,x_n)$ be a random sample from a distribution with some parametric PDF $p(x;\theta^\circ), x\in R^N$, where $\theta^0=(\theta_1^0,...,\theta_m^0)\in\Theta\subseteq R^m$ are unknown parameters to be estimated.

By definition **Fisher Likelihood Function** is a PDF of sample *X* whilst θ is true:

$$L(\theta)=p(X;\theta)=\prod_{l=1}^{n} p(x_l;\theta). \qquad (4.1.4)$$

By definition **Logarithmic Likelihood Function** is a function:

$$l(\theta)::=\ln L(\theta)=\sum_{l=1}^{n}\ln p(x_l;\theta), \qquad (4.1.5)$$

where $L(\theta)$ describes the probability to get the sample X given θ, or in other words $L(\theta)$ characterizes the likelihood level of θ and $l(\theta)$ is a monotonous function of $L(\theta)$ that on one hand linearizes the multiplications of probabilities and on the other hand does not influence extremum of $L(\theta)$. **Maximal Likelihood Estimator** (MML) – is an estimator that maximizes $L(\theta)$ ($l(\theta)$):

$$\widehat{\theta^0} = \arg\max_{\theta}\left(l(\theta)\right) = \arg\max_{\theta}\left(L(\theta)\right), \theta \in \Theta \subseteq R^m. \tag{4.1.6}$$

Thus, the following algorithm might be addressed for $\hat{\theta}$ estimation:

Step 1: Solve: $\frac{d}{d\theta_j}(l(\theta)) = 0, j = \overline{1,m}$ with respect to θ.

Step 2: Choose points that satisfy the local maximum condition $\frac{d^2}{d\theta_j^2}(l(\theta)) < 0, j = \overline{1,m}$.

Step 3: Enumerate all local maximums and **choose** the global one.

Properties of MML estimator**:**

- Consistency;
- Asymptotical Normality;
- Asymptotical Efficiency;
- Might be biased.

Least Squares Method (LSE)

Let a random experiment observing a random value $\eta \in R^1$ dependent on non-random value $x \in R^m$ so that the following equation holds true:

$$\eta = f\left(x;\theta^\circ\right) + \varepsilon, \tag{4.1.7}$$

where x – is an independent variable (factor, regressor), η – is a dependent random variable, $\theta^\circ = \left(\theta_j^\circ\right) \in \Theta \subseteq R^m$ – is a vector of unknown parameters, $\varepsilon \in R^1$ – is a random error, so that $E\{\varepsilon\} = 0, D\{\varepsilon\} = \sigma^2 < +\infty, E\left\{\varepsilon_i\varepsilon_j\right\} = \delta_{ij}\sigma^2$. Such a model is known as regressive model. In order to estimate θ° and σ^2 n independent experiments are carried out: in every experiment given some x_i, $\eta = y_i$ is observed, in other words: $y_i = f\left(x_i;\theta^\circ\right) + \varepsilon_i, i = \overline{1,n}$. By definition (4.1.8) **is known as the residual** of i-th experiment.

$$\xi_i = y_i - f\left(x_i;\theta\right). \tag{4.1.8}$$

$$R^2(\theta)=\sum_{i=1}^{n}(\xi_i)^2=\sum_{i=1}^{n}\left(y_i-f(x_i;\theta)\right)^2, \tag{4.1.9}$$

(4.1.9) is known as a sum of squared residuals or R-squared. The idea of LSM is to choose a value of estimator of θ° so as to minimize R-squared (4.1.10).

$$\hat{\theta}=\arg\min R^2(\theta). \tag{4.1.10}$$

Let the following matrix definitions:

$Y=\left(y_1,...,y_n\right)'$, $X=\begin{pmatrix} x_{11} & ... & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & ... & x_{nm} \end{pmatrix}$, $\varepsilon=\left(\varepsilon_1,...,\varepsilon_n\right)'$. Then the model becomes (4.1.11)

$$Y=X\theta^\circ+\varepsilon, \tag{4.1.11}$$

provided that $E\{\varepsilon\}=0, E\left\{\varepsilon\varepsilon^T\right\}=\sigma^2 E_n$.

Theorem 7.1.1 Let (4.1.7*), so that $\left|X^T X\right|\neq 0$. Then a LSE estimator is unique and is equal to $\widehat{\theta^\circ}=CY, C=(X^T X)^{-1}X^T$.

Proof: (4.1.10) <=> $\varepsilon\varepsilon^T=\left(Y-X\theta^\circ\right)\left(Y-X\theta^\circ\right)^T\xrightarrow[\theta^\circ]{}\min$ <=> $2X^T\left(X\theta^\circ-Y\right)=0$

<=> $$\widehat{\theta^\circ}=(X^T X)^{-1}X^T Y. \tag{4.1.12}$$

Note $\widehat{\theta^\circ}$ - is an unbiased estimator with the following covariance matrix: $V\{\hat{\theta}\}=\sigma^2(X^T X)^{-1}$.

Properties of LSE estimator, $\left|X^T X\right|\neq 0, E\{\varepsilon\}=0, E\left\{\varepsilon\varepsilon^T\right\}=\sigma^2 E_n$ **:**

- Unbiased;
- Efficient;
- If in addition errors belong to a normal distribution then LSE estimators are also MML estimators.

4.2 Representing time series with ARIMA models

ARIMA is an autoregressive (noted as **AR**IMA) integrated (noted as AR**I**MA) moving average model (noted as ARI**MA**) first introduced by Box et al. (1976); ARIMA is indicated by means of the notation $\text{ARIMA}(p,d,q)$ where

p – is the order of the autoregressive process (AR)
d – is the order of the differencing (I)
q – is the order of the moving-average process (MA)

Given a time series $Y_t,\ t = 1, 2, ..., n$, representing for instance significant wave heights or wave directions over a certain time horizon ARIMA model can be expressed in terms of the backshift operator L as:

$$(1-L)^d Y_t = \mu + \frac{\theta(L)}{\phi(L)}\varepsilon_t, \tag{4.2.1}$$

where

t - is the time index;
μ - is a constant;
L - is the backshift operator : $LY_t=Y_{t-1}$;
$\emptyset(L)$ - is the autoregressive operator :

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p; \tag{4.2.2}$$

$\theta(L)$ - is the moving –average operator :

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_p L^p; \tag{4.2.3}$$

ε_t -is a random error distributed with $N(0,\sigma^2)$ distribution, note that its normality is not required for long-term time series, however zero – mean is essential.

ARIMA model assumes:

1. $(1-L)^d Y_t$ should be a stationary stochastic process so that parameter d is the minimum order of taking differences of Y_t so as to make this process stationary or in other words Y_t to be d-difference stationary stochastic process, where d is the minimum order of integration to make Y_t stationary. Stationarity of a stochastic process means that the joint CDF of n variables from the given time series is not dependent on the shift:

$$\begin{aligned}&F_{t_1,t_2,\ldots,t_n}((1-L)^d Y_1,(1-L)^d Y_2,\ldots,(1-L)^d Y_n)=\\&=F_{t_1+k,t_2+k,\ldots,t_n+k}((1-L)^d Y_1,(1-L)^d Y_2,\ldots,(1-L)^d Y_n),k\in\mathbb{Z}\end{aligned},\qquad(4.2.4)$$

$$\begin{aligned}&F_{t_1,t_2,\ldots,t_n}((1-L)^b Y_1,(1-L)^b Y_2,\ldots,(1-L)^b Y_n)\neq\\&\neq F_{t_1+k,t_2+k,\ldots,t_n+k}((1-L)^b Y_1,(1-L)^b Y_2,\ldots,(1-L)^b Y_n),k\in\mathbb{Z},b=\overline{0,\ldots d-1}\end{aligned}.\qquad(4.2.5)$$

Note that in most applications only weak stationarity is required, which means:

$$\begin{cases}\mu_t((1-L)^d Y_t)=const,k\in\mathbb{Z}\\K(1-L)^d Y(z,s)=K(1-L)^d Y(z-s)\end{cases},\qquad(4.2.6)$$

where $Kw(s,z)$ is the autocorrelation function of a stochastic process w. F is the joint CDF for the corresponding set of random variables from the corresponding process and $\mu_t(w_t)$ is the mean value of time series w_t.

1.1. In terms of the defined above $\text{ARIMA}(p,d,q)$ model stationarity of time series is equivalent to having roots of the equation: $1-\phi_1\lambda-\phi_2\lambda^2-\cdots-\phi_p\lambda^p=0$, smaller than one: $|\lambda_i|<1\ \forall i=\overline{1,\ldots p}$.

1.2. Note, that stationarity and order of integration of time series are tested by means of different unit root tests, among which most popular tests are Dickey-Fuller and Augmented Dickey-Fuller tests.

2. Estimates of the parameters of the model must be statistically significant (T-test, F-test should be addressed).

3. Residuals of the model must be white noise or in other words independent random variables. This is tested by means of ACF and PACF analysis. The most widely used statistical test is the Ljung-Box test.

4. Residuals must be distributed within the same distribution function with a zero mean and constant variance, note that only for short time series their normality is strongly required. Normality might be tested by means of Kolmogorov-Smirnov, Jarque-Berra and other statistical tests.

5. Principle of parsimony, based on AIC and SC statistics as well as RSS analysis could be addressed to choose the best model among the significant one, so that the smaller AIC and SC are the better the model is and the greater RSS is the better the model is.

4.3 Clustering of time series data

K-means clustering

K-means algorithm of intergroup means described by MacQueen, J. B. (1967) is based on the idea of minimizing sum of squares of distances to the centroid of cluster belonging to that cluster. This procedure is based on calculation of *k* intergroup means and consists of the following steps:

Step 1: *k* initial cluster centroids $z_1(l), z_2(l), \ldots, z_k(l)$ **are selected**. This choice is made either randomly or with respect to some deterministic (or some heuristic) rule. It is convenient to use first *k* results from the sample of the given set of objects.

Step 2: At *n*-th iteration of the algorithm members of the given set of objects {X} **are assigned** to *k* clusters according to the following rule:

$$x \in S_j(n),\ \ j = \arg\min_i(\|x - z_i(n)\|), i = \overline{1,k}\,, \tag{4.3.1}$$

where $S_j(n)$ is the set of objects, belonging to the cluster with $z_j(n)$ as its centroid. In case there is multiple choice for *j,* any solution of $j = \arg\min_i(\|x - z_i(n)\|), i = \overline{1,k}$ might be chosen either randomly or deterministically (or by means of some heuristics).

Step 3: New cluster centroids **are determined** basing on the results from step 2, $z_j(n+1), j = \overline{1,k}$, so as to minimize the sum of squares of distances between the objects belonging to the corresponding cluster $S_j(n)$ and corresponding cluster centroids. In other words:

$$z_j(n+1) = \arg\min_{y \in S_j(n)}\left(\sum_{x \in S_j(n)} \|x - y\|^2\right), j = \overline{1,k}\,, \tag{4.3.2}$$

$z_j(n+1)$ - minimizes the corresponding sum of squares is the mean of set $S_j(n)$. Thus it can be claimed that:

$$z_j(n+1) = \frac{1}{\| S_j(n) \|}\sum_{x \in S_j(n)} x, \quad j = \overline{1,k}\,. \tag{4.3.3}$$

Step 4: Algorithm **is finished** as soon as: $z_j(n+1) = z_j(n)\ \forall j = \overline{1,k}$.

4.4 *Data description*

Studied data is represented by time series of 3 hour frequent observations of significant wave heights and wave directions collected at different locations of the Norwegian continental shelf from 06:00 of 01.09.1957 to 18:00 of 30.06.2013 and thus forming 152928 observations for each parameter at each location. Locations are specified by latitude and longitude degrees. Graphical representation of significant wave height time series are shown in Figures 1 and 2.

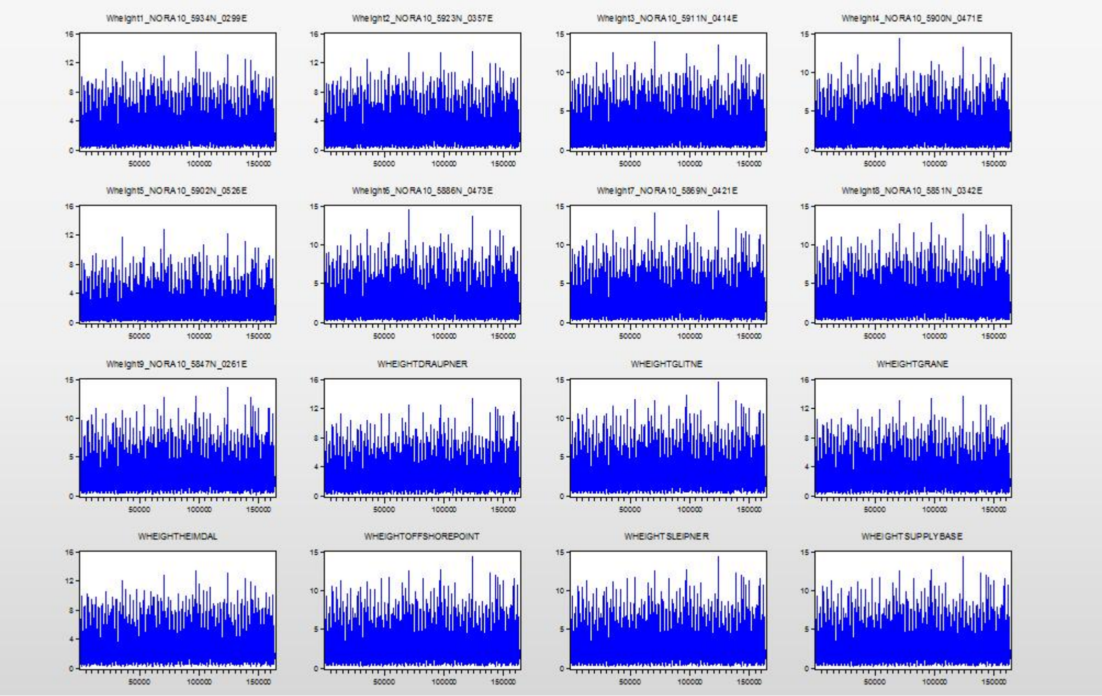


Figure 1. *Significant wave heights time series*

Regarding significant wave heights one can notice presence of seasonality within the observation so that during some seasons the mean of significant wave heights is greater than during other seasons, the latter is relevant for every year from the given dataset. Moreover significant wave heights data seem to be both non-stationary even with regard to the mean (as a result of its seasonality) and heteroscedastic with regard to variance. Concerning wave directions it should be mentioned that these data parameters are quite difficult to analyze and handle in a raw form due to their circularity; that is why we will first make some preliminary data transformation to linearize the data. This is achieved by making projections of wave direction angles on some artificial XY De Cart axes (4.4.1).

$$\begin{cases} wd_{x,t} = 1\cos(wd_t) \\ wd_{y,t} = 1\cos(90 - wd_t) \end{cases} . \qquad (4.4.1)$$

A sample of resulting time series is represented in Figure 3. The inverse data transformation is carried out as described in formula (4.4.2)

$$wd_t = \arctan 2(wd_{y,t}, wd_{x,t}) . \tag{4.4.2}$$

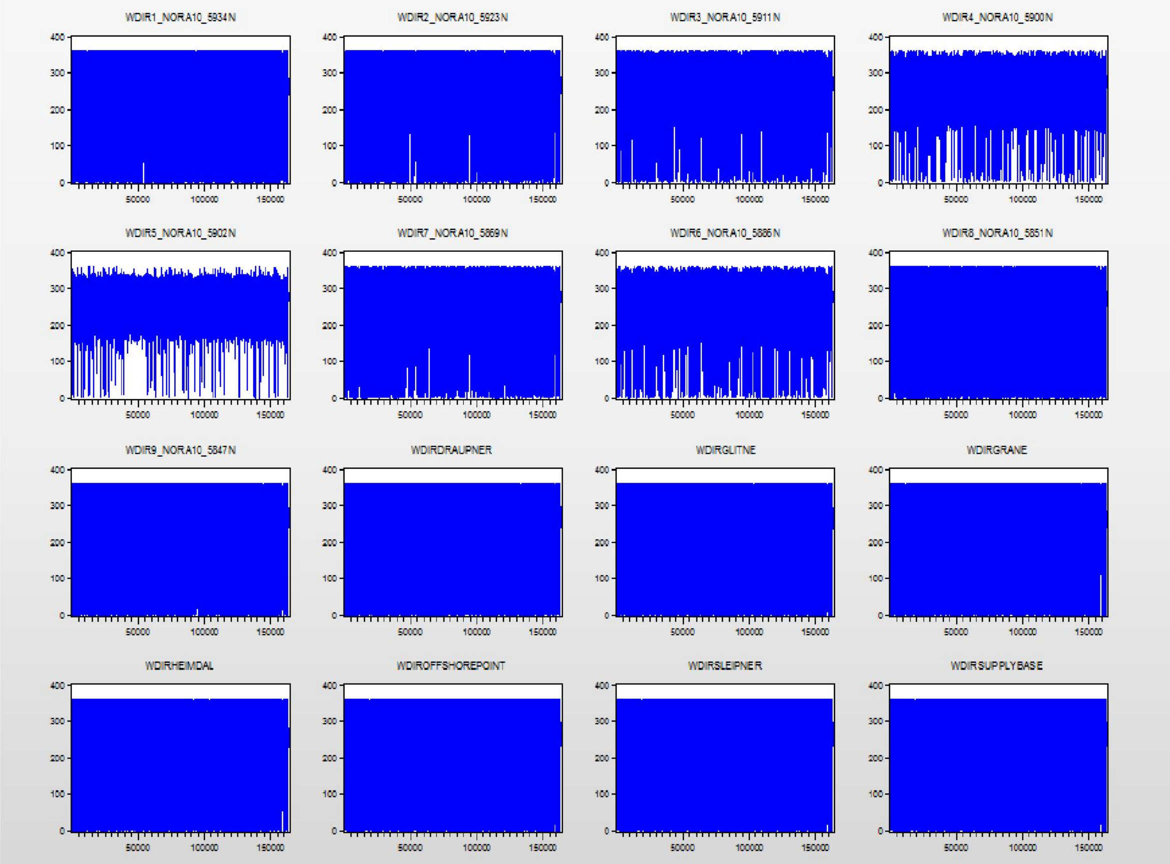


Figure 2. *Wave direction time series*

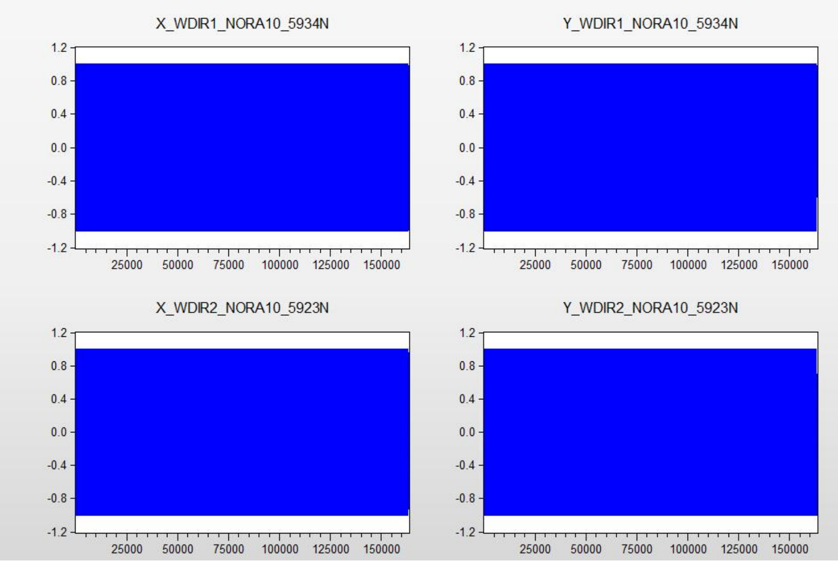


Figure 3. *A sample of decomposed wave direction time series*

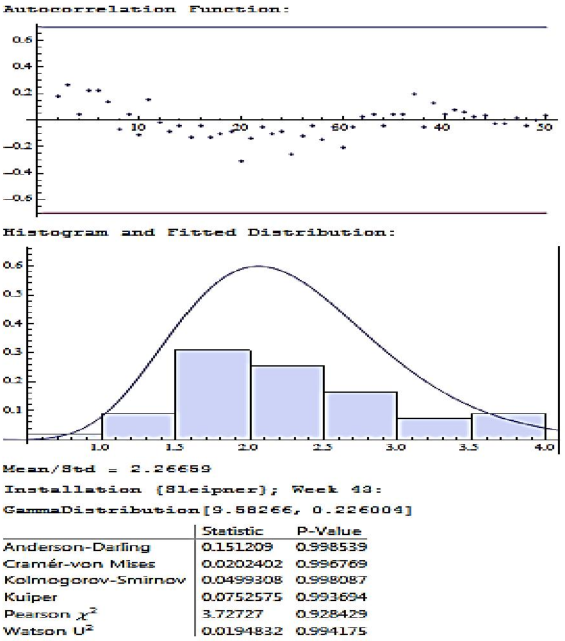
4.5 Statistical distributions analysis

Statistical data analysis for fitting distributions of significant wave heights and their clustering with regard to parameters of these distribution was carried out. Initially time series were aggregated over weeks for each of 52 weeks of the year over the years by means of C# code, so that:

$$w_{i,y,w}^{d} = \frac{1}{56} \sum_{d,h \in W_w} w_{i,y,d,h}^{d}, i \in \{I\}, y = \overline{1955, 2012}, w = \overline{1, 52}, W = \{week_1, ..., week_{52}\}, \qquad (4.5.1)$$

where set *I* consists of such elements as Sleipner, Grane, Glitne, Heimdal, and Draupner.

Afterwards MML (Maximal Likelihood Method) method, described above, was applied so as to fit $Gamma(\alpha, \beta)$ distribution with two parameters α and β (Hazewinkel and Michiel 2001). This was achieved by means of Wolfram Mathematica 8.0 for students' script. This script is represented in listing A-1 in the appendix. The output of this model in graphical form looks as presented in Figure 4 below (Sleipner location significant wave heights analysis for week 43 is presented) and includes estimates of parameters of Gamma distribution, autocorrelation function in graphical form, histogram of the observations and results of statistical tests for the fitted distribution.

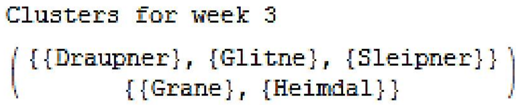


```
Mean/Std = 2.26659
Installation {Sleipner}; Week 43:
GammaDistribution[9.58266, 0.226004]
```

	Statistic	P-Value
Anderson-Darling	0.151209	0.998539
Cramér-von Mises	0.0202402	0.996769
Kolmogorov-Smirnov	0.0499308	0.998087
Kuiper	0.0752575	0.993694
Pearson χ^2	3.72727	0.928429
Watson U^2	0.0194832	0.994175

Figure 4. *Statistical distributions analysis of SWH for Sleipner at week 43*

Clustering results based on k-means algorithm with respect to math expectation divided by standard deviation of the corresponding distribution – $\frac{\mu}{\sigma}$ parameter for each week's distributions has also been carried out. An example for such output is presented below:



```
Clusters for week 3
( {{Draupner}, {Glitne}, {Sleipner}} )
(        {{Grane}, {Heimdal}}        )
```

Figure 5. *Clustering based on distributions of SWH at the installations at week 43*

The results for Gamma distribution fitting at all locations are generalized in Table 1, whilst the results for cluster analysis for each of 52 weeks are presented in Table 2.

This approach of SWH modelling has one major disadvantage that sampling from a distribution does not consider autocorrelations between real life random events of SWH. In other words, route durations as well as weather at different locations are assumed to be independent random varibales (functions) whereas in practice these random variables are dependent on both time (e.g. on *n* previous random varibales of weather state) and space (weather at Grane should be correlated with weather at Heimdal). In further research, random variables will be replaced by stochastic processes of weather parameters.

Week	Drauner			Glitne			Grane			Heimdal			Sleipner		
No.	a	b	P-Val.	a	b	P-Val.	a	b	P-Val.	a	b	P-Val.	a	b	P-Val.
1	13.74	0.23	0.96	14.02	0.23	0.95	13.43	0.24	0.94	13.31	0.25	0.89	13.81	0.23	0.95
2	17.65	0.17	0.82	17.28	0.17	0.97	16.71	0.18	0.93	16.93	0.18	0.97	17.46	0.17	0.90
3	18.86	0.17	0.81	19.57	0.17	0.77	18.70	0.18	0.78	19.12	0.17	0.79	19.37	0.16	0.76
4	11.53	0.27	0.98	12.16	0.27	0.92	11.98	0.28	0.98	12.15	0.27	1.00	11.89	0.26	0.96
5	10.39	0.31	0.35	10.50	0.31	0.34	10.14	0.33	0.38	10.29	0.32	0.38	10.34	0.31	0.31
6	9.96	0.32	0.95	10.58	0.31	0.89	10.81	0.31	0.99	11.46	0.29	1.00	10.28	0.31	0.93
7	10.64	0.31	0.73	9.94	0.34	0.80	9.31	0.37	0.76	9.28	0.37	0.65	10.29	0.32	0.73
8	7.23	0.41	1.00	7.57	0.40	1.00	7.32	0.42	0.99	7.71	0.41	0.99	7.47	0.39	1.00
9	12.40	0.23	0.98	12.66	0.23	0.92	11.83	0.26	0.72	12.04	0.26	0.64	12.78	0.22	0.92
10	6.41	0.47	0.86	6.90	0.44	0.81	6.94	0.45	0.88	7.20	0.44	0.84	6.59	0.45	0.87
11	7.33	0.39	0.87	7.57	0.39	0.85	7.09	0.43	0.75	7.23	0.43	0.73	7.49	0.38	0.88
12	9.48	0.32	0.82	10.07	0.31	0.90	10.31	0.30	0.98	10.78	0.29	0.98	9.76	0.31	0.80
13	9.96	0.30	0.71	10.21	0.30	0.80	10.55	0.29	0.73	10.86	0.29	0.72	10.01	0.30	0.78
14	8.76	0.33	0.88	8.66	0.34	0.88	8.26	0.36	0.92	8.43	0.36	0.95	8.67	0.33	0.90
15	12.02	0.23	0.86	12.14	0.23	0.93	11.83	0.25	0.99	11.53	0.26	0.99	12.08	0.23	0.90
16	8.90	0.30	0.63	8.86	0.31	0.67	8.38	0.33	0.70	8.40	0.34	0.65	8.84	0.30	0.63
17	6.25	0.43	0.55	6.12	0.45	0.68	6.02	0.47	0.70	6.13	0.46	0.68	6.18	0.43	0.63
18	7.28	0.33	0.76	7.66	0.32	0.78	8.04	0.31	0.86	8.33	0.31	0.85	7.45	0.32	0.72
19	10.88	0.21	0.97	10.35	0.22	0.94	10.40	0.23	1.00	10.33	0.23	0.99	10.52	0.21	0.94
20	11.06	0.21	1.00	10.59	0.22	0.92	10.07	0.24	0.88	10.15	0.24	0.85	10.97	0.21	0.99
21	6.18	0.34	0.66	6.43	0.33	0.65	6.68	0.33	0.78	6.91	0.32	0.79	6.24	0.33	0.64
22	7.70	0.25	0.95	8.41	0.23	0.96	8.71	0.22	0.93	8.94	0.22	0.94	8.06	0.23	0.97
23	6.91	0.25	1.00	7.33	0.24	0.99	7.50	0.24	0.98	7.58	0.25	0.98	7.01	0.25	0.99
24	8.45	0.21	0.38	8.73	0.21	0.42	9.15	0.20	0.64	9.31	0.20	0.77	8.54	0.21	0.36
25	9.65	0.17	0.75	10.02	0.16	0.88	10.15	0.17	0.97	9.79	0.18	0.99	9.65	0.16	0.80
26	7.68	0.21	0.96	8.48	0.20	0.92	8.67	0.20	0.85	9.19	0.19	0.81	8.08	0.20	0.95
27	9.77	0.17	0.97	10.32	0.16	0.92	11.11	0.15	0.98	11.11	0.15	0.99	9.95	0.16	0.94
28	10.08	0.16	0.67	11.10	0.14	0.74	11.13	0.14	0.69	11.47	0.14	0.87	10.69	0.14	0.74
29	13.97	0.11	0.96	15.43	0.10	0.95	17.08	0.09	0.83	16.98	0.10	0.55	14.30	0.11	0.97
30	9.11	0.16	0.57	9.74	0.15	0.64	10.10	0.15	0.73	9.84	0.16	0.83	9.26	0.16	0.60
31	8.44	0.18	0.94	9.38	0.16	0.93	10.09	0.16	0.90	10.52	0.15	0.95	8.80	0.17	0.93
32	12.18	0.12	0.87	12.74	0.11	0.77	13.22	0.11	0.82	13.18	0.11	0.69	12.47	0.11	0.78
33	10.19	0.14	0.90	11.23	0.12	0.88	12.18	0.12	0.94	12.66	0.11	0.89	10.53	0.13	0.85
34	11.75	0.14	0.96	13.42	0.12	0.97	13.77	0.12	0.92	15.11	0.11	0.87	12.78	0.12	0.94
35	11.07	0.12	0.97	12.88	0.10	0.89	13.66	0.10	0.95	13.30	0.10	0.94	11.65	0.11	0.87
36	7.84	0.18	0.91	8.65	0.16	0.83	9.41	0.15	0.79	9.88	0.14	0.74	8.14	0.17	0.88
37	8.05	0.20	0.99	8.58	0.18	0.98	8.74	0.19	0.97	8.89	0.19	0.98	8.26	0.19	1.00
38	8.14	0.19	0.81	9.09	0.17	0.75	9.09	0.18	0.80	9.26	0.17	0.95	8.55	0.18	0.75
39	8.97	0.19	0.97	9.61	0.17	0.97	9.49	0.18	0.95	9.67	0.18	0.87	9.38	0.17	0.97
40	6.99	0.25	0.85	7.31	0.24	0.92	7.37	0.25	0.95	7.50	0.25	0.97	7.09	0.24	0.87
41	7.50	0.26	0.55	8.05	0.25	0.46	8.62	0.24	0.43	9.02	0.23	0.39	7.77	0.25	0.48
42	11.12	0.18	0.72	10.90	0.18	0.70	10.87	0.19	0.76	10.56	0.19	0.82	10.87	0.18	0.75
43	9.45	0.23	1.00	10.26	0.22	0.98	10.93	0.21	0.96	10.69	0.21	0.97	9.58	0.23	1.00
44	10.14	0.23	1.00	10.52	0.23	0.98	10.88	0.22	0.92	10.86	0.23	0.88	10.23	0.23	0.99
45	7.54	0.31	0.86	7.79	0.30	0.92	8.06	0.30	1.00	8.07	0.30	1.00	7.54	0.30	0.87
46	11.04	0.23	0.81	11.58	0.22	0.71	12.15	0.22	0.80	12.75	0.21	0.56	11.23	0.23	0.77
47	13.61	0.19	0.40	15.51	0.17	0.49	16.01	0.17	0.87	16.10	0.17	0.84	14.46	0.18	0.37
48	12.48	0.22	0.92	13.07	0.21	0.99	12.80	0.23	0.98	12.75	0.23	1.00	12.70	0.21	0.95
49	10.26	0.28	0.98	11.40	0.26	0.96	12.45	0.24	0.96	13.02	0.23	0.88	10.63	0.27	0.96
50	10.84	0.27	0.85	11.95	0.25	0.93	12.20	0.25	0.96	12.81	0.24	0.96	11.26	0.26	0.87
51	9.60	0.31	0.89	9.72	0.31	0.85	10.14	0.30	0.88	10.42	0.29	0.89	9.56	0.30	0.87
52	13.94	0.22	0.99	15.46	0.20	0.92	15.69	0.20	0.86	15.85	0.20	0.80	14.53	0.20	0.98

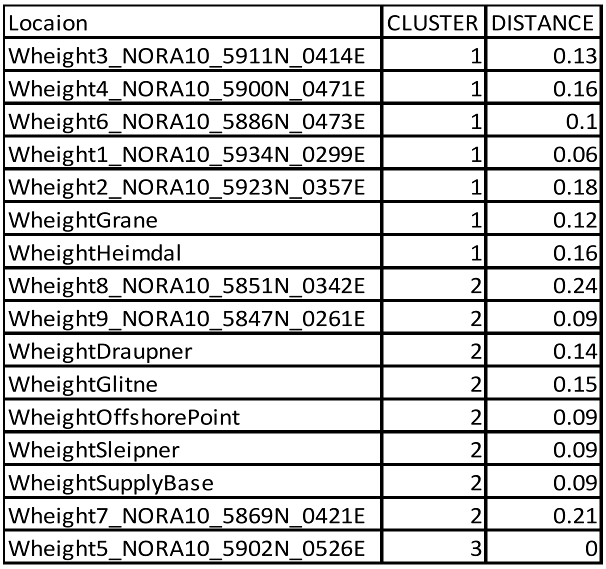
Table 1. *Statistical distributions analysis of SWH for five installations*

Week No.	Clusters' structure
1	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
2	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
3	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
4	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
5	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
6	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
7	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
8	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
9	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
10	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
11	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
12	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
13	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
14	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
15	{{{Draupner},{Sleipner}},{{Glitne}},{{Grane},{Heimdal}}}
16	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
17	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
18	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
19	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
20	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
21	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
22	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
23	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
24	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
25	{{{Draupner},{Sleipner}},{{Glitne},{Grane},{Heimdal}}}
26	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
27	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
28	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
29	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
30	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
31	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
32	{{{Draupner},{Grane},{Heimdal}},{{Glitne},{Sleipner}}}
33	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
34	{{{Draupner},{Grane},{Heimdal}},{{Glitne},{Sleipner}}}
35	{{{Draupner},{Glitne}},{{Grane},{Heimdal}},{{Sleipner}}}
36	{{{Draupner},{Glitne}},{{Grane},{Heimdal}},{{Sleipner}}}
37	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
38	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
39	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
40	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
41	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
42	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
43	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
44	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
45	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
46	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
47	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
48	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
49	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
50	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
51	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}
52	{{{Draupner},{Glitne},{Sleipner}},{{Grane},{Heimdal}}}

Table 2. *Clustering based on parameters of distributions of SWH for 5 installations*

4.6 K-means data clustering

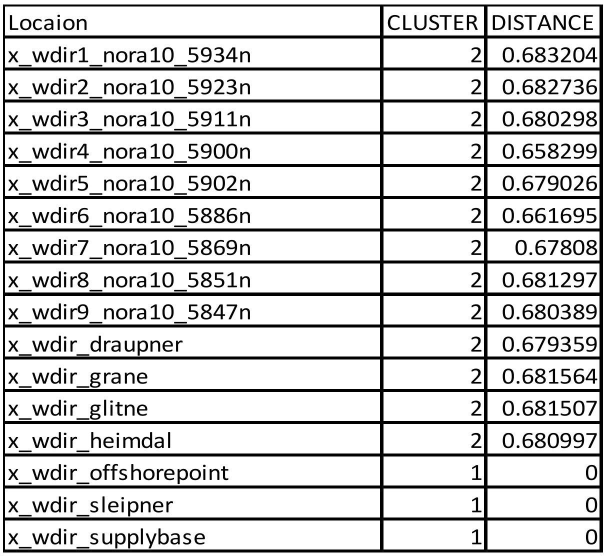
By the time we began time series analysis we managed to get data for some additional 11 points of the relevant grid. Since we then had 16 geographical points it seemed reasonable to carry out some data clustering and further data aggregation so as to reduce the amount of almost identical models addressed. After carrying out correlation analysis of time series between geographical points and several runs of k-means clustering algorithm minimizing intergroup distances with different amounts of clusters, it has been decided that significant wave heights should be divided into 3 clusters, whereas both axes of wave directions should be divided into 2 clusters. The results of k-means clustering algorithm applied to these time series are shown in the Tables 3-5 below:



Locaion	CLUSTER	DISTANCE
Wheight3_NORA10_5911N_0414E	1	0.13
Wheight4_NORA10_5900N_0471E	1	0.16
Wheight6_NORA10_5886N_0473E	1	0.1
Wheight1_NORA10_5934N_0299E	1	0.06
Wheight2_NORA10_5923N_0357E	1	0.18
WheightGrane	1	0.12
WheightHeimdal	1	0.16
Wheight8_NORA10_5851N_0342E	2	0.24
Wheight9_NORA10_5847N_0261E	2	0.09
WheightDraupner	2	0.14
WheightGlitne	2	0.15
WheightOffshorePoint	2	0.09
WheightSleipner	2	0.09
WheightSupplyBase	2	0.09
Wheight7_NORA10_5869N_0421E	2	0.21
Wheight5_NORA10_5902N_0526E	3	0

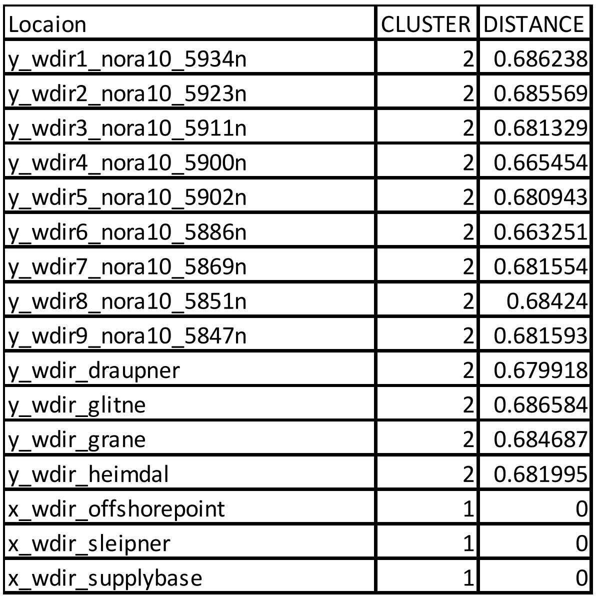
Table 3. *Significant wave height clustering (by distance we mean the distance from the corresponding cluster's centroid)*

It is worth noticing that surprisingly clusters for both axes of wave directions are equivalent, which makes it a way easier to carry out the inverse-transformation of data after having them modelled.



Locaion	CLUSTER	DISTANCE
x_wdir1_nora10_5934n	2	0.683204
x_wdir2_nora10_5923n	2	0.682736
x_wdir3_nora10_5911n	2	0.680298
x_wdir4_nora10_5900n	2	0.658299
x_wdir5_nora10_5902n	2	0.679026
x_wdir6_nora10_5886n	2	0.661695
x_wdir7_nora10_5869n	2	0.67808
x_wdir8_nora10_5851n	2	0.681297
x_wdir9_nora10_5847n	2	0.680389
x_wdir_draupner	2	0.679359
x_wdir_grane	2	0.681564
x_wdir_glitne	2	0.681507
x_wdir_heimdal	2	0.680997
x_wdir_offshorepoint	1	0
x_wdir_sleipner	1	0
x_wdir_supplybase	1	0

Table 4. *X- axe wave direction clustering*



Locaion	CLUSTER	DISTANCE
y_wdir1_nora10_5934n	2	0.686238
y_wdir2_nora10_5923n	2	0.685569
y_wdir3_nora10_5911n	2	0.681329
y_wdir4_nora10_5900n	2	0.665454
y_wdir5_nora10_5902n	2	0.680943
y_wdir6_nora10_5886n	2	0.663251
y_wdir7_nora10_5869n	2	0.681554
y_wdir8_nora10_5851n	2	0.68424
y_wdir9_nora10_5847n	2	0.681593
y_wdir_draupner	2	0.679918
y_wdir_glitne	2	0.686584
y_wdir_grane	2	0.684687
y_wdir_heimdal	2	0.681995
x_wdir_offshorepoint	1	0
x_wdir_sleipner	1	0
x_wdir_supplybase	1	0

Table 5. *Y- axe wave direction clustering*

4.7 ARIMA modelling

First data aggregation among the clusters has been carried out by means of the corresponding rules:

$$\overset{\frown}{w}_{c,y,m,d,h,t} = \frac{1}{\| c \|}\sum_{i\in c} w_{i,y,m,d,h,t}, c \in C, \qquad (4.7.1)$$

where $w_{i,y,m,d,h}$ is an observation from the original time series, C = $\{c_1, c_2, \ldots, c_n\}$ - is a set of clusters for the corresponding time series, y, m, d, h are year, month, day and hour of an observation correspondingly, *t* is the weather type index, $t \in \{SWH, WD_x, WD_y\}$.

After the initial research of the data aggregated over clusters it has been decided to try modelling weather parameters for averages of the corresponding observations over the years. Considering data aggregating in time dimension, it should be mentioned that every observation during the year is aggregated over all available years by taking corresponding averages, so that we transformed from 152928 to 2928 observations, namely 2928 = (366*24)/3, with respect to the rule (4.7.2).

$$\tilde{w}_{c,m,d,h,t} = \frac{1}{\| \{w_{y,m,d,h,t}\}, w_{y,m,d,h,t} \notin \varnothing \|}\sum_{y=y_0}^{Y} \overset{\frown}{w}_{c,y,m,d,h,t}. \qquad (4.7.2)$$

Obviously, in this case we got a certain phenomenon for 29th of February, since the aggregation is not that smooth for this day, which is the result of the fact that data is aggregated over 4 times less observations for this day, however 29th of February was finally not considered at the stage of final time series analysis. This was achieved by means of seasonal decomposition: (471 +-8)-th observation, which corresponds to the 29th of February (471*3/24 ≈ 59 = 31 + 28) is considered to be the edge between winter and summer periods (as might be seen in the further analysis).

All time-series afterwards have been tested for stationarity and occurred to be I(1) in accordance with Augmented Dickey-Fuller test. However taking first differences (4.7.3) solves the occurred problem only for wave directions data.

$$\bar{d}_{c,m,d,h,t} = \tilde{w}_{c,m,d,h+3,t} - \tilde{w}_{c,m,d,h,t}. \qquad (4.7.3)$$

It does not let us get rid of heteroscedasticity and seasonality of data for significant wave heights, thence transformation (4.7.4) has been applied for these time series:

$$\bar{v}_{c,m,d,h,t} = \ln\left(\frac{\tilde{w}_{c,m,d,h+3,t}}{\tilde{w}_{c,m,d,h,t}}\right). \qquad (4.7.4)$$

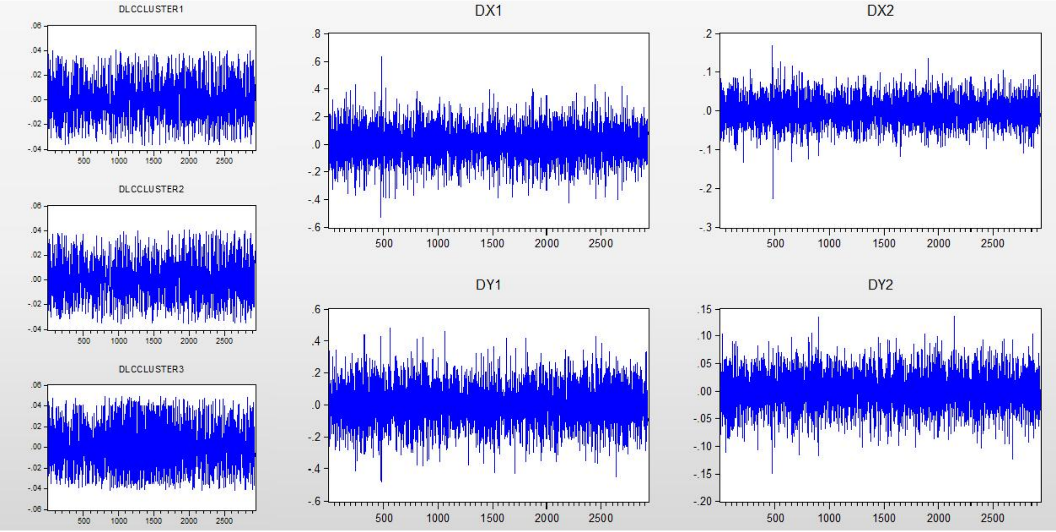
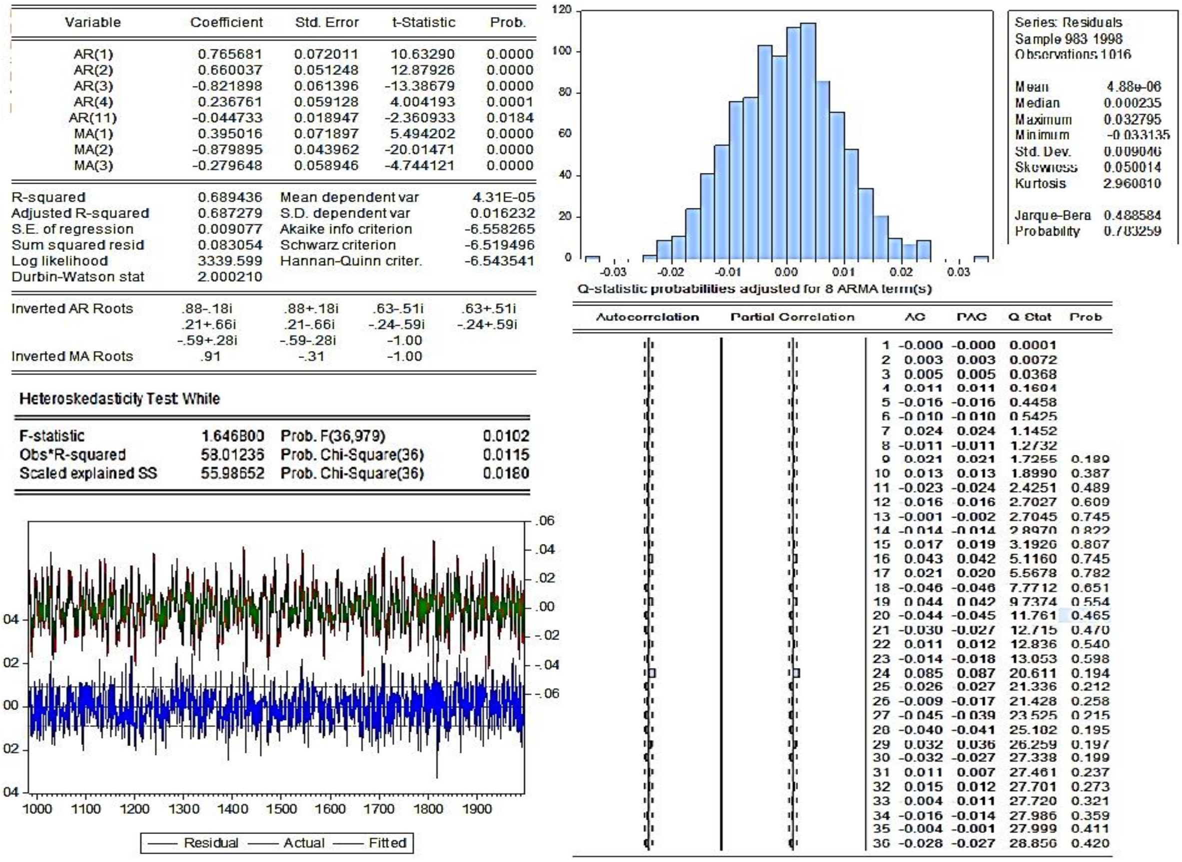


Figure 6. *Aggregated over clusters and years and transformed time series*

Significant wave heights data remains heteroscedastic even after the proper transformation done, hence its seasonal decomposition was additionally carried out (ARCH and GARCH analysis was considered as an alternative, however it was by far over-performed by seasonal decomposition in terms of White-test (ARCH-test), Ljung-Box test and SC, AIC analysis), whereas wave directions data was modelled for the whole season. As one can see all of the classical assumptions of ARIMA models, mentioned above, are satisfied: the residuals are independent (according to Ljung-Box Test), they cannot be rejected to be normally distributed in most cases (according to Jarque-Berra test), however note that the last is not essential for long time series with a mean of error close to 0 and constant variance of error terms; there also is no significant heteroscedasticity of the residuals according to White (Arch) Test. One can also pay attention to the fit-graphs of modelled and real data, presented in the reports below (see Figures 7-20).

Significant wave heights at each cluster are decomposed into several seasons. One can refer to Table 6 with more detailed description of seasonal decomposition of the data at the very end of the section.

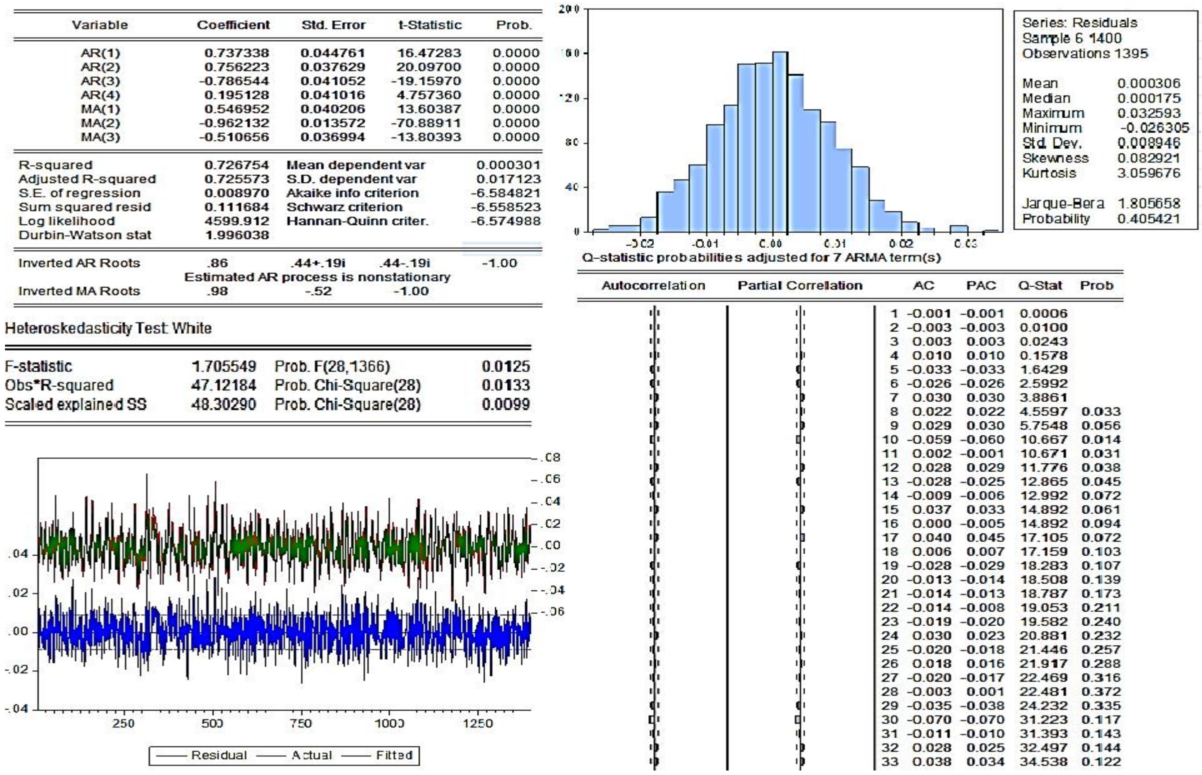


```
Variable        Coefficient   Std. Error   t-Statistic   Prob.

AR(1)            0.765681     0.072011     10.63290     0.0000
AR(2)            0.660037     0.051248     12.87926     0.0000
AR(3)           -0.821898     0.061396    -13.38679     0.0000
AR(4)            0.236761     0.059128     4.004193     0.0001
AR(11)          -0.044733     0.018947    -2.360933     0.0184
MA(1)            0.395016     0.071897     5.494202     0.0000
MA(2)           -0.879895     0.043962    -20.01471     0.0000
MA(3)           -0.279648     0.058946    -4.744121     0.0000

R-squared            0.689436   Mean dependent var     4.31E-05
Adjusted R-squared   0.687279   S.D. dependent var     0.016232
S.E. of regression   0.009077   Akaike info criterion -6.558265
Sum squared resid    0.083054   Schwarz criterion     -6.519496
Log likelihood       3339.599   Hannan-Quinn criter.  -6.543541
Durbin-Watson stat   2.000210

Inverted AR Roots   .88-.18i    .88+.18i    .63-.51i    .63+.51i
                    .21+.66i    .21-.66i   -.24-.59i   -.24+.59i
                   -.59+.28i   -.59-.28i     -1.00
Inverted MA Roots      .91         -.31       -1.00

Heteroskedasticity Test: White

F-statistic          1.646800   Prob. F(36,979)          0.0102
Obs*R-squared        58.01236   Prob. Chi-Square(36)     0.0115
Scaled explained SS  55.98652   Prob. Chi-Square(36)     0.0180
```

```
Series: Residuals
Sample 983 1998
Observations 1016

Mean        4.88e-06
Median      0.000235
Maximum     0.032795
Minimum    -0.033135
Std. Dev.   0.009046
Skewness    0.050014
Kurtosis    2.960010

Jarque-Bera 0.488584
Probability 0.783259
```

```
Q-statistic probabilities adjusted for 8 ARMA term(s)

Autocorrelation  Partial Correlation      AC     PAC    Q-Stat  Prob

                                     1 -0.000 -0.000  0.0001
                                     2  0.003  0.003  0.0072
                                     3  0.005  0.005  0.0368
                                     4  0.011  0.011  0.1604
                                     5 -0.016 -0.016  0.4458
                                     6 -0.010 -0.010  0.5425
                                     7  0.024  0.024  1.1452
                                     8 -0.011 -0.011  1.2732
                                     9  0.021  0.021  1.7255  0.189
                                    10  0.013  0.013  1.8990  0.387
                                    11 -0.023 -0.024  2.4251  0.489
                                    12  0.016  0.016  2.7027  0.609
                                    13 -0.001 -0.002  2.7045  0.745
                                    14 -0.014 -0.014  2.8970  0.822
                                    15  0.017  0.019  3.1926  0.867
                                    16  0.043  0.042  5.1160  0.745
                                    17  0.021  0.020  5.5678  0.782
                                    18 -0.046 -0.046  7.7712  0.651
                                    19  0.044  0.042  9.7374  0.554
                                    20 -0.044 -0.045  11.761  0.465
                                    21 -0.030 -0.027  12.715  0.470
                                    22  0.011  0.012  12.836  0.540
                                    23 -0.014 -0.018  13.053  0.598
                                    24  0.085  0.087  20.611  0.194
                                    25  0.026  0.027  21.336  0.212
                                    26 -0.009 -0.017  21.428  0.258
                                    27 -0.045 -0.039  23.525  0.215
                                    28 -0.040 -0.041  25.102  0.195
                                    29  0.032  0.036  26.259  0.197
                                    30 -0.032 -0.027  27.338  0.199
                                    31  0.011  0.007  27.461  0.237
                                    32  0.015  0.012  27.701  0.273
                                    33  0.004  0.011  27.720  0.321
                                    34 -0.016 -0.014  27.986  0.359
                                    35 -0.004 -0.001  27.999  0.411
                                    36 -0.028 -0.027  28.856  0.420
```

Figure 7. *Report on summer model for cluster 1 of significant wave heights*

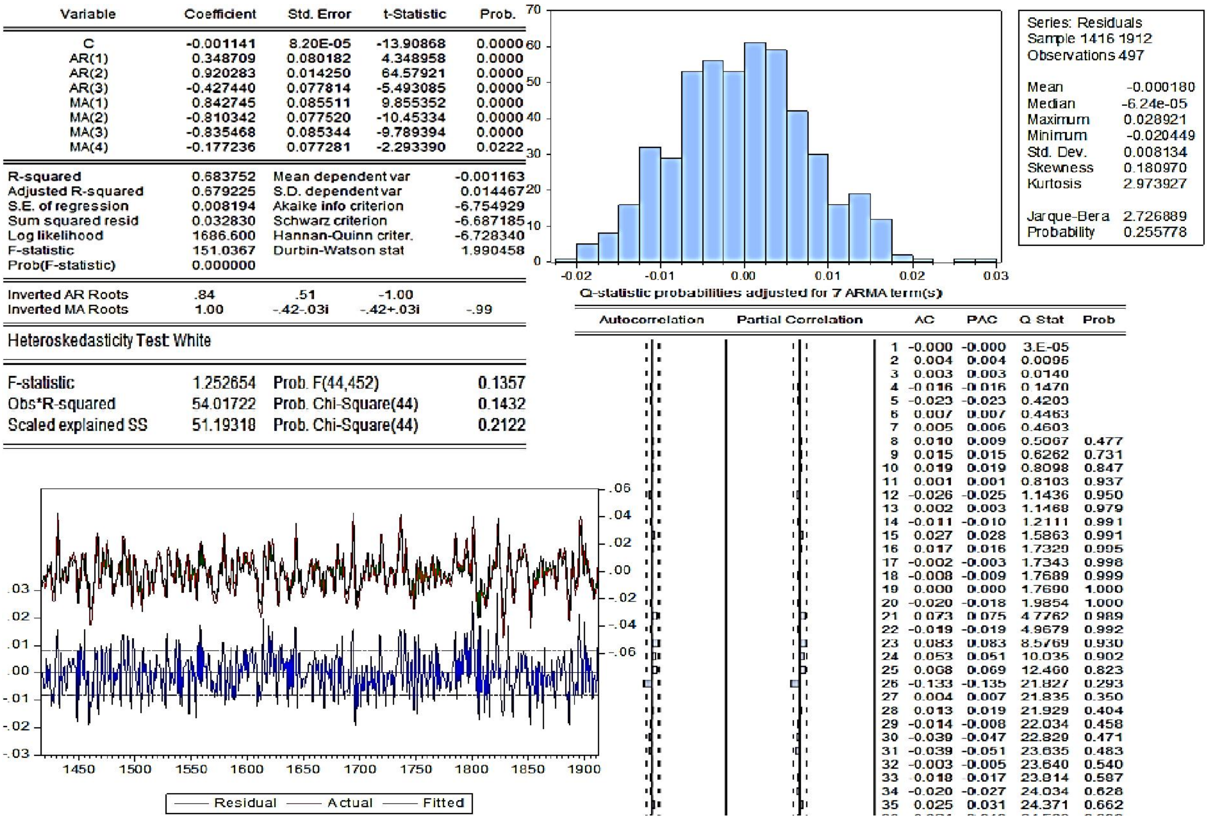


```
Variable        Coefficient   Std. Error   t-Statistic   Prob.

AR(1)            0.737338     0.044761     16.47283     0.0000
AR(2)            0.756223     0.037629     20.09700     0.0000
AR(3)           -0.786544     0.041052    -19.15970     0.0000
AR(4)            0.195128     0.041016     4.757360     0.0000
MA(1)            0.546952     0.040206     13.60387     0.0000
MA(2)           -0.962132     0.013572    -70.88911     0.0000
MA(3)           -0.510656     0.036994    -13.80393     0.0000

R-squared            0.726754   Mean dependent var     0.000301
Adjusted R-squared   0.725573   S.D. dependent var     0.017123
S.E. of regression   0.008970   Akaike info criterion -6.584821
Sum squared resid    0.111684   Schwarz criterion     -6.558523
Log likelihood       4599.912   Hannan-Quinn criter.  -6.574988
Durbin-Watson stat   1.996038

Inverted AR Roots      .86       .44+.19i    .44-.19i      -1.00
                    Estimated AR process is nonstationary
Inverted MA Roots      .98         -.52       -1.00

Heteroskedasticity Test: White

F-statistic          1.705549   Prob. F(28,1366)         0.0125
Obs*R-squared        47.12184   Prob. Chi-Square(28)     0.0133
Scaled explained SS  48.30290   Prob. Chi-Square(28)     0.0099
```

```
Series: Residuals
Sample 6 1400
Observations 1395

Mean         0.000306
Median       0.000175
Maximum      0.032593
Minimum     -0.026305
Std. Dev.    0.008946
Skewness     0.082921
Kurtosis     3.059676

Jarque-Bera  1.805658
Probability  0.405421
```

```
Q-statistic probabilities adjusted for 7 ARMA term(s)

Autocorrelation  Partial Correlation      AC     PAC    Q-Stat  Prob

                                     1 -0.001 -0.001  0.0006
                                     2 -0.003 -0.003  0.0100
                                     3  0.003  0.003  0.0243
                                     4  0.010  0.010  0.1578
                                     5 -0.033 -0.033  1.6429
                                     6 -0.026 -0.026  2.5992
                                     7  0.030  0.030  3.8861
                                     8  0.022  0.022  4.5597  0.033
                                     9  0.029  0.030  5.7548  0.056
                                    10 -0.059 -0.060  10.667  0.014
                                    11  0.002 -0.001  10.671  0.031
                                    12  0.028  0.029  11.776  0.038
                                    13 -0.028 -0.025  12.865  0.045
                                    14 -0.009 -0.006  12.992  0.072
                                    15  0.037  0.033  14.892  0.061
                                    16  0.000 -0.005  14.892  0.094
                                    17  0.040  0.045  17.105  0.072
                                    18  0.006  0.007  17.159  0.103
                                    19 -0.028 -0.029  18.283  0.107
                                    20 -0.013 -0.014  18.508  0.139
                                    21 -0.014 -0.013  18.787  0.173
                                    22 -0.014 -0.008  19.053  0.211
                                    23 -0.019 -0.020  19.582  0.240
                                    24  0.030  0.023  20.881  0.232
                                    25 -0.020 -0.018  21.446  0.257
                                    26  0.018  0.016  21.917  0.288
                                    27 -0.020 -0.017  22.469  0.316
                                    28 -0.003  0.001  22.481  0.372
                                    29 -0.035 -0.038  24.232  0.335
                                    30 -0.070 -0.070  31.223  0.117
                                    31 -0.011 -0.010  31.393  0.143
                                    32  0.028  0.025  32.497  0.144
                                    33  0.038  0.034  34.538  0.122
```

Figure 8. *Report on winter 1 model for cluster 1 of significant wave heights*

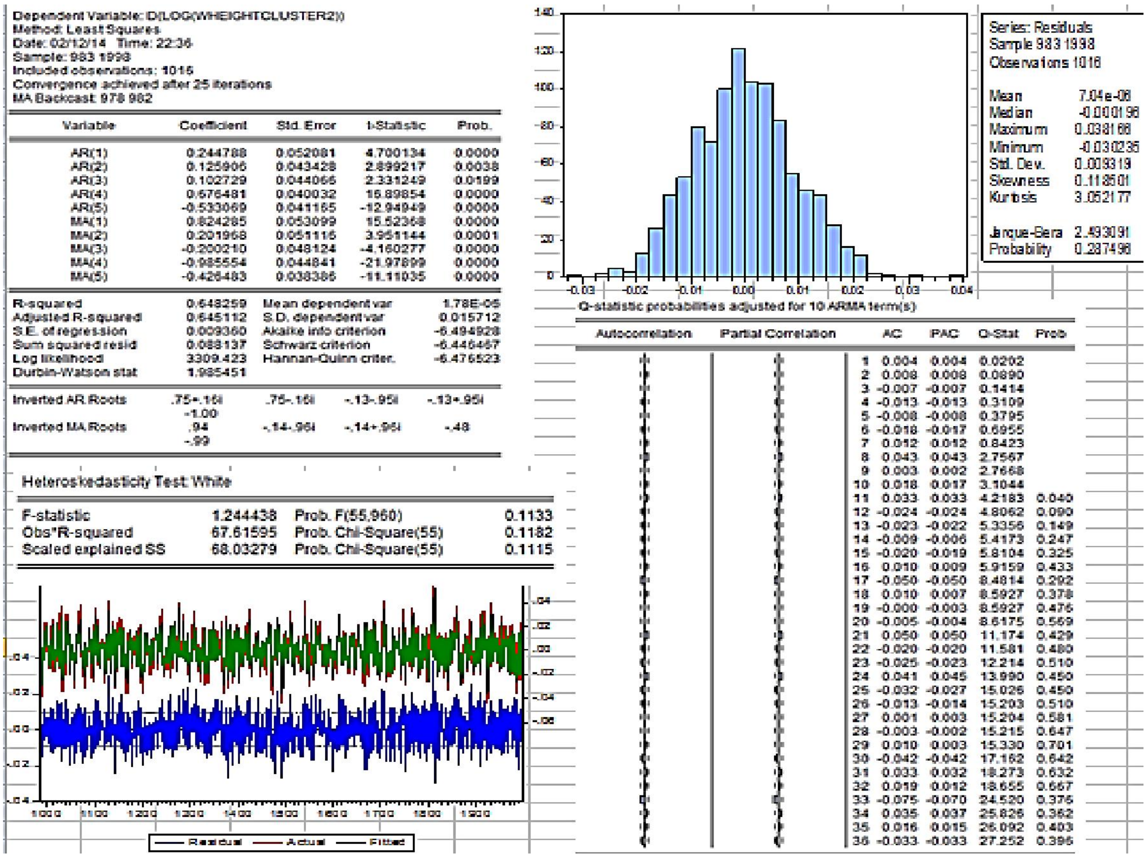


```
Variable        Coefficient    Std. Error    t-Statistic    Prob.

C               -0.001141      8.20E-05      -13.90868      0.0000
AR(1)            0.348709      0.080182       4.348958      0.0000
AR(2)            0.920283      0.014250       64.57921      0.0000
AR(3)           -0.427440      0.077814      -5.493085      0.0000
MA(1)            0.842745      0.085511       9.855352      0.0000
MA(2)           -0.810342      0.077520      -10.45334      0.0000
MA(3)           -0.835468      0.085344      -9.789394      0.0000
MA(4)           -0.177236      0.077281      -2.293390      0.0222

R-squared            0.683752   Mean dependent var     -0.001163
Adjusted R-squared   0.679225   S.D. dependent var      0.014467
S.E. of regression   0.008194   Akaike info criterion  -6.754929
Sum squared resid    0.032830   Schwarz criterion      -6.687185
Log likelihood       1686.600   Hannan-Quinn criter.   -6.728340
F-statistic          151.0367   Durbin-Watson stat      1.990458
Prob(F-statistic)    0.000000

Inverted AR Roots    .84        .51          -1.00
Inverted MA Roots    1.00      -.42-.03i     -.42+.03i     -.99

Heteroskedasticity Test: White

F-statistic          1.252654   Prob. F(44,452)          0.1357
Obs*R-squared        54.01722   Prob. Chi-Square(44)     0.1432
Scaled explained SS  51.19318   Prob. Chi-Square(44)     0.2122
```

```
Series: Residuals
Sample 1416 1912
Observations 497

Mean         -0.000180
Median       -6.24e-05
Maximum       0.028921
Minimum      -0.020449
Std. Dev.     0.008134
Skewness      0.180970
Kurtosis      2.973927

Jarque-Bera   2.726889
Probability   0.255778
```

```
Q-statistic probabilities adjusted for 7 ARMA term(s)

Autocorrelation   Partial Correlation        AC      PAC     Q-Stat   Prob

                                        1  -0.000  -0.000   3.E-05
                                        2   0.004   0.004   0.0095
                                        3   0.003   0.003   0.0140
                                        4  -0.016  -0.016   0.1470
                                        5  -0.023  -0.023   0.4203
                                        6   0.007   0.007   0.4463
                                        7   0.005   0.006   0.4603
                                        8   0.010   0.009   0.5067   0.477
                                        9   0.015   0.015   0.6262   0.731
                                       10   0.019   0.019   0.8098   0.847
                                       11   0.001   0.001   0.8103   0.937
                                       12  -0.026  -0.025   1.1436   0.950
                                       13   0.002   0.003   1.1468   0.979
                                       14  -0.011  -0.010   1.2111   0.991
                                       15   0.027   0.028   1.5863   0.991
                                       16   0.017   0.016   1.7329   0.995
                                       17  -0.002  -0.003   1.7343   0.998
                                       18  -0.008  -0.009   1.7689   0.999
                                       19   0.000   0.000   1.7690   1.000
                                       20  -0.020  -0.018   1.9854   1.000
                                       21   0.073   0.075   4.7762   0.989
                                       22  -0.019  -0.019   4.9679   0.992
                                       23   0.083   0.083   8.5769   0.930
                                       24   0.053   0.051   10.035   0.902
                                       25   0.068   0.069   12.460   0.823
                                       26  -0.133  -0.135   21.827   0.293
                                       27   0.004   0.007   21.835   0.350
                                       28   0.013   0.019   21.929   0.404
                                       29  -0.014  -0.008   22.034   0.458
                                       30  -0.039  -0.047   22.829   0.471
                                       31  -0.039  -0.051   23.635   0.483
                                       32  -0.003  -0.005   23.640   0.540
                                       33   0.018   0.017   23.814   0.587
                                       34  -0.020  -0.027   24.034   0.628
                                       35   0.025   0.031   24.371   0.662
```

Figure 9. *Report on winter 2 model for cluster 1 of significant wave heights*

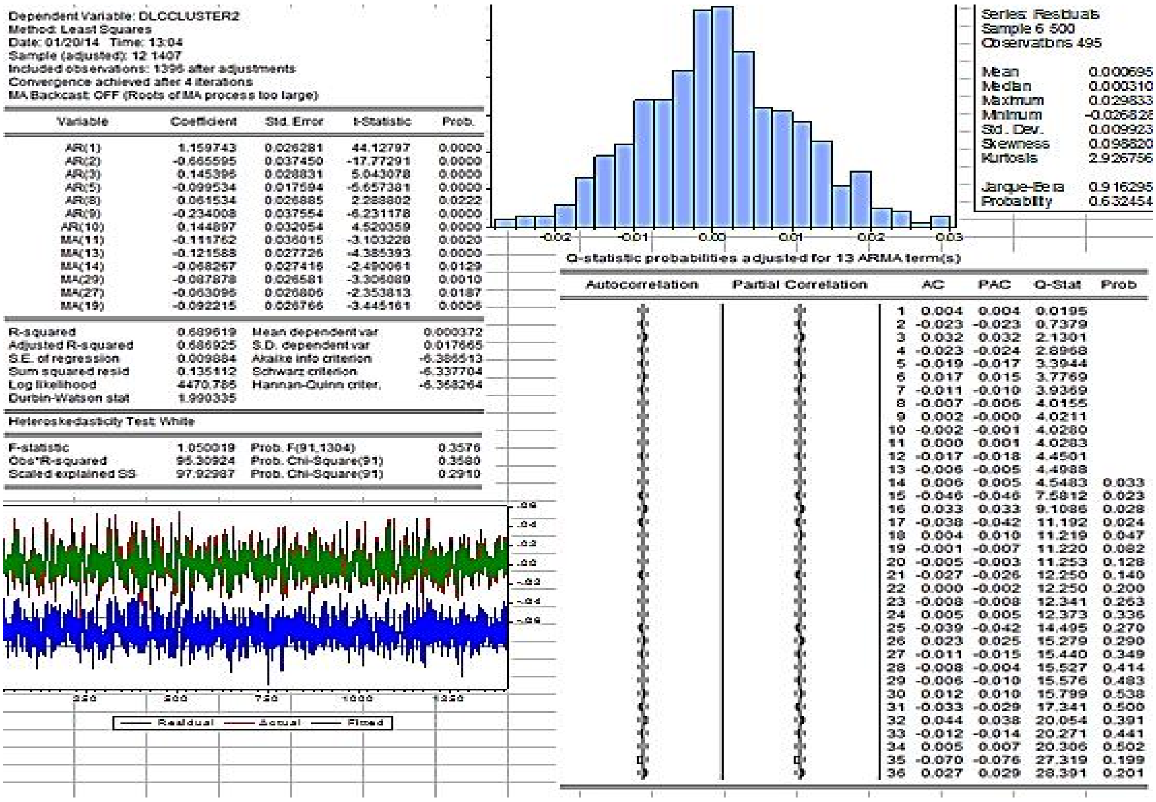


```
Dependent Variable: D(LOG(WHEIGHTCLUSTER2))
Method: Least Squares
Date: 02/12/14   Time: 22:36
Sample: 983 1998
Included observations: 1016
Convergence achieved after 25 iterations
MA Backcast: 978 982

Variable        Coefficient    Std. Error    t-Statistic    Prob.

AR(1)            0.244788      0.052081       4.700134      0.0000
AR(2)            0.125906      0.043428       2.899217      0.0038
AR(3)            0.102729      0.044066       2.331249      0.0199
AR(4)            0.676481      0.040032       16.89854      0.0000
AR(5)           -0.533069      0.041165      -12.94949      0.0000
MA(1)            0.824285      0.053099       15.52368      0.0000
MA(2)            0.201968      0.051116       3.951144      0.0001
MA(3)           -0.200210      0.048124      -4.160277      0.0000
MA(4)           -0.985554      0.044841      -21.97899      0.0000
MA(5)           -0.426483      0.038386      -11.11035      0.0000

R-squared            0.648259   Mean dependent var      1.78E-05
Adjusted R-squared   0.645112   S.D. dependent var      0.015712
S.E. of regression   0.009360   Akaike info criterion  -6.494928
Sum squared resid    0.088137   Schwarz criterion      -6.446467
Log likelihood       3309.423   Hannan-Quinn criter.   -6.476523
Durbin-Watson stat   1.985451

Inverted AR Roots    .75+.16i     .75-.16i     -.13-.95i     -.13+.95i
                     -1.00
Inverted MA Roots    .94         -.14-.96i     -.14+.96i     -.48
                     -.99

Heteroskedasticity Test: White

F-statistic          1.244438   Prob. F(55,960)          0.1133
Obs*R-squared        67.61595   Prob. Chi-Square(55)     0.1182
Scaled explained SS  68.03279   Prob. Chi-Square(55)     0.1115
```

```
Series: Residuals
Sample 983 1998
Observations 1016

Mean          7.04e-08
Median       -0.000198
Maximum       0.038168
Minimum      -0.030235
Std. Dev.     0.009319
Skewness      0.118501
Kurtosis      3.052177

Jarque-Bera   2.493091
Probability   0.287498
```

```
Q-statistic probabilities adjusted for 10 ARMA term(s)

Autocorrelation   Partial Correlation        AC      PAC     Q-Stat   Prob

                                        1   0.004   0.004   0.0202
                                        2   0.008   0.008   0.0890
                                        3  -0.007  -0.007   0.1414
                                        4  -0.013  -0.013   0.3109
                                        5  -0.008  -0.008   0.3795
                                        6  -0.018  -0.017   0.6955
                                        7   0.012   0.012   0.8423
                                        8   0.043   0.043   2.7567
                                        9   0.003   0.002   2.7668
                                       10   0.018   0.017   3.1044
                                       11   0.033   0.033   4.2183   0.040
                                       12  -0.024  -0.024   4.8062   0.090
                                       13  -0.023  -0.022   5.3356   0.149
                                       14  -0.009  -0.006   5.4173   0.247
                                       15  -0.020  -0.019   5.8104   0.325
                                       16   0.010   0.009   5.9159   0.433
                                       17  -0.050  -0.050   8.4814   0.292
                                       18   0.010   0.007   8.5927   0.378
                                       19  -0.000  -0.003   8.5927   0.476
                                       20  -0.005  -0.004   8.6175   0.569
                                       21   0.050   0.050   11.174   0.429
                                       22  -0.020  -0.020   11.581   0.480
                                       23  -0.025  -0.023   12.214   0.510
                                       24   0.041   0.045   13.990   0.450
                                       25  -0.032  -0.027   15.026   0.450
                                       26  -0.013  -0.014   15.203   0.510
                                       27   0.001   0.003   15.204   0.581
                                       28  -0.003  -0.002   15.215   0.647
                                       29   0.010   0.003   15.330   0.701
                                       30  -0.042  -0.042   17.162   0.642
                                       31   0.033   0.032   18.273   0.632
                                       32   0.019   0.012   18.655   0.667
                                       33  -0.075  -0.070   24.520   0.376
                                       34   0.035   0.037   25.826   0.362
                                       35   0.016   0.015   26.092   0.403
                                       36  -0.033  -0.033   27.252   0.396
```

Figure 10. *Report on summer model for cluster 2 of significant wave heights*

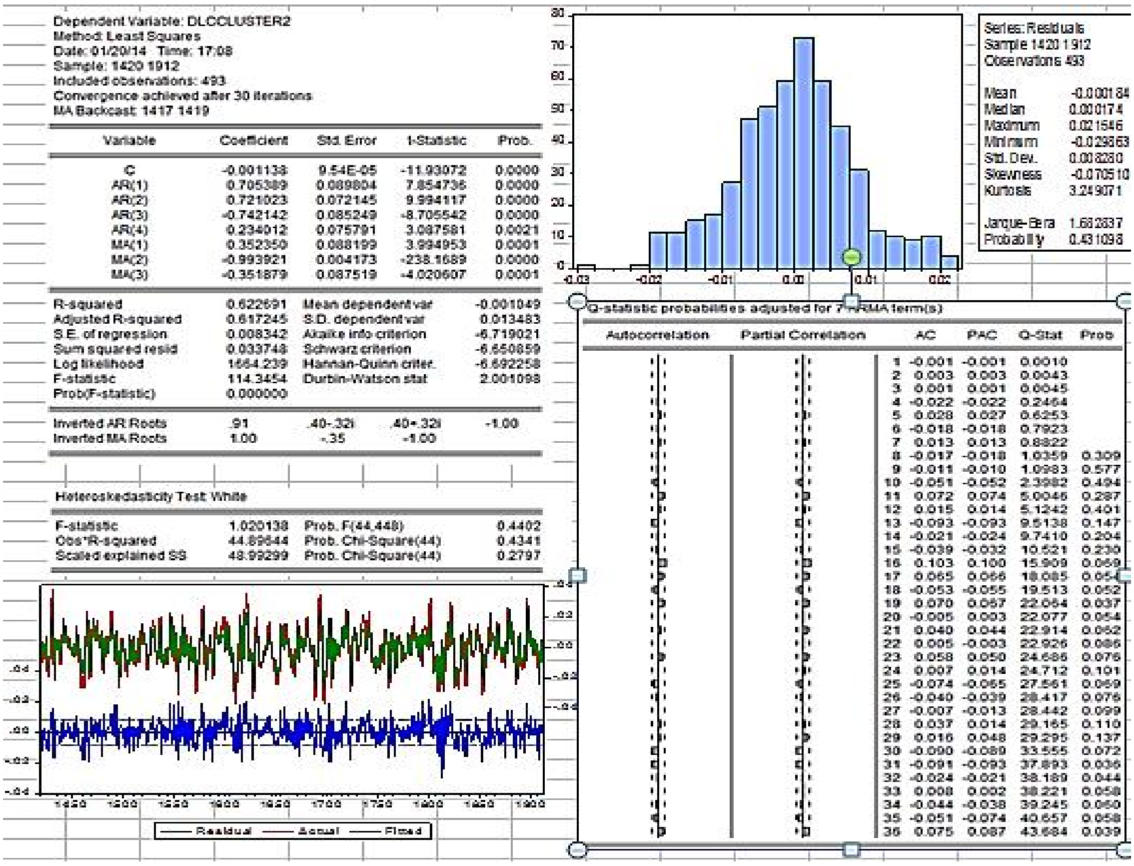


```
Dependent Variable: DLCCLUSTER2
Method: Least Squares
Date: 01/20/14   Time: 13:04
Sample (adjusted): 12 1407
Included observations: 1396 after adjustments
Convergence achieved after 4 iterations
MA Backcast: OFF (Roots of MA process too large)

        Variable      Coefficient   Std. Error   t-Statistic    Prob.

          AR(1)        1.159743     0.026281     44.12797     0.0000
          AR(2)       -0.665595     0.037450    -17.77291     0.0000
          AR(3)        0.145396     0.028831     5.043078     0.0000
          AR(5)       -0.099534     0.017594    -5.657381     0.0000
          AR(8)        0.061534     0.026885     2.288802     0.0222
          AR(9)       -0.234008     0.037554    -6.231178     0.0000
         AR(10)        0.144897     0.032054     4.520359     0.0000
         MA(11)       -0.111762     0.036015    -3.103228     0.0020
         MA(13)       -0.121568     0.027726    -4.385393     0.0000
         MA(14)       -0.068267     0.027416    -2.490061     0.0129
         MA(29)       -0.087878     0.026581    -3.306089     0.0010
         MA(27)       -0.063096     0.026806    -2.353813     0.0187
         MA(19)       -0.092215     0.026766    -3.445161     0.0006

R-squared               0.689619   Mean dependent var       0.000372
Adjusted R-squared      0.686925   S.D. dependent var       0.017665
S.E. of regression      0.009884   Akaike info criterion   -6.386513
Sum squared resid       0.135112   Schwarz criterion       -6.337704
Log likelihood          4470.786   Hannan-Quinn criter.    -6.368264
Durbin-Watson stat      1.990335

Heteroskedasticity Test: White

F-statistic             1.050019   Prob. F(91,1304)           0.3576
Obs*R-squared           95.30924   Prob. Chi-Square(91)       0.3580
Scaled explained SS     97.92987   Prob. Chi-Square(91)       0.2910
```

```
Series: Residuals
Sample 6 500
Observations 495

Mean          0.000695
Median        0.000310
Maximum       0.029833
Minimum      -0.02682
Std. Dev.     0.009923
Skewness      0.096820
Kurtosis      2.926756

Jarque-Bera   0.916295
Probability   0.632454
```

```
Q-statistic probabilities adjusted for 13 ARMA term(s)

Autocorrelation   Partial Correlation       AC     PAC    Q-Stat   Prob

                                       1   0.004   0.004  0.0195
                                       2  -0.023  -0.023  0.7379
                                       3   0.032   0.032  2.1301
                                       4  -0.023  -0.024  2.8968
                                       5  -0.019  -0.017  3.3944
                                       6   0.017   0.015  3.7769
                                       7  -0.011  -0.010  3.9369
                                       8  -0.007  -0.006  4.0155
                                       9   0.002  -0.000  4.0211
                                      10  -0.002  -0.001  4.0280
                                      11   0.000   0.001  4.0283
                                      12  -0.017  -0.018  4.4501
                                      13  -0.006  -0.005  4.4988
                                      14   0.006   0.005  4.5483  0.033
                                      15  -0.046  -0.046  7.5812  0.023
                                      16   0.033   0.033  9.1086  0.028
                                      17  -0.038  -0.042  11.192  0.024
                                      18   0.004   0.010  11.219  0.047
                                      19  -0.001  -0.007  11.220  0.082
                                      20  -0.005  -0.003  11.253  0.128
                                      21  -0.027  -0.026  12.250  0.140
                                      22   0.000  -0.002  12.250  0.200
                                      23  -0.008  -0.008  12.341  0.263
                                      24   0.005   0.005  12.373  0.336
                                      25  -0.039  -0.042  14.495  0.270
                                      26   0.023   0.025  15.279  0.290
                                      27  -0.011  -0.015  15.440  0.349
                                      28  -0.008  -0.004  15.527  0.414
                                      29  -0.006  -0.010  15.576  0.483
                                      30   0.012   0.010  15.799  0.538
                                      31  -0.033  -0.029  17.341  0.500
                                      32   0.044   0.038  20.054  0.391
                                      33  -0.012  -0.014  20.271  0.441
                                      34   0.005   0.007  20.306  0.502
                                      35  -0.070  -0.076  27.319  0.199
                                      36   0.027   0.029  28.391  0.201
```

Figure 11. *Report on winter 1 model for cluster 2 of significant wave heights*

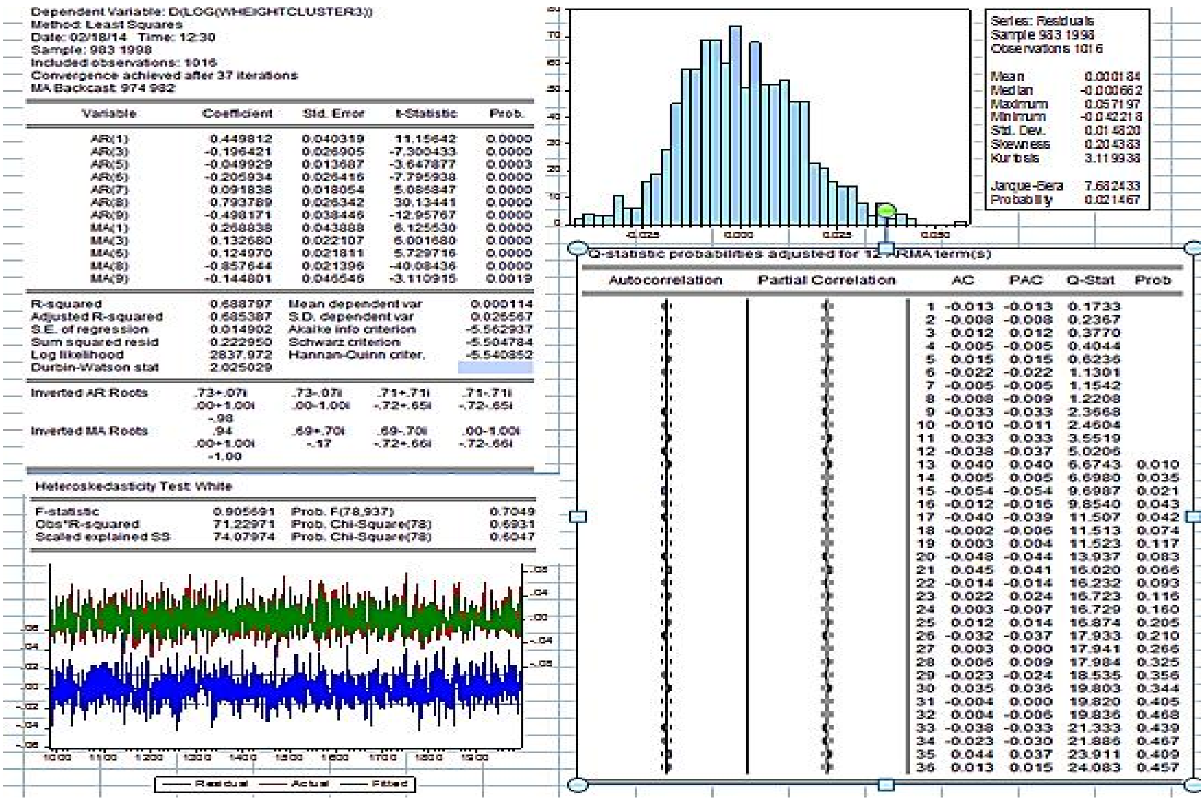


```
Dependent Variable: DLCCLUSTER2
Method: Least Squares
Date: 01/20/14   Time: 17:08
Sample: 1420 1912
Included observations: 493
Convergence achieved after 30 iterations
MA Backcast: 1417 1419

        Variable      Coefficient   Std. Error   t-Statistic    Prob.

              C       -0.001138     9.54E-05    -11.93072     0.0000
          AR(1)        0.705389     0.089804     7.854736     0.0000
          AR(2)        0.721023     0.072145     9.994117     0.0000
          AR(3)       -0.742142     0.085249    -8.705542     0.0000
          AR(4)        0.234012     0.075791     3.087581     0.0021
          MA(1)        0.352350     0.088199     3.994953     0.0001
          MA(2)       -0.993921     0.004173    -238.1689     0.0000
          MA(3)       -0.351879     0.087519    -4.020607     0.0001

R-squared               0.622691   Mean dependent var      -0.001049
Adjusted R-squared      0.617245   S.D. dependent var       0.013483
S.E. of regression      0.008342   Akaike info criterion   -6.719021
Sum squared resid       0.033748   Schwarz criterion       -6.650859
Log likelihood          1664.239   Hannan-Quinn criter.    -6.692258
F-statistic             114.3454   Durbin-Watson stat       2.001098
Prob(F-statistic)       0.000000

Inverted AR Roots          .91        .40-.32i      .40+.32i      -1.00
Inverted MA Roots         1.00          -.35         -1.00

Heteroskedasticity Test: White

F-statistic             1.020138   Prob. F(44,448)            0.4402
Obs*R-squared           44.89644   Prob. Chi-Square(44)       0.4341
Scaled explained SS     48.99299   Prob. Chi-Square(44)       0.2797
```

```
Series: Residuals
Sample 1420 1912
Observations 493

Mean         -0.000184
Median        0.000174
Maximum       0.021546
Minimum      -0.029363
Std. Dev.     0.008280
Skewness     -0.070510
Kurtosis      3.249071

Jarque-Bera   1.682837
Probability   0.431098
```

```
Q-statistic probabilities adjusted for 7 ARMA term(s)

Autocorrelation   Partial Correlation       AC     PAC    Q-Stat   Prob

                                       1  -0.001  -0.001  0.0010
                                       2   0.003   0.003  0.0043
                                       3   0.001   0.001  0.0045
                                       4  -0.022  -0.022  0.2464
                                       5   0.028   0.027  0.6253
                                       6  -0.018  -0.018  0.7923
                                       7   0.013   0.013  0.8822
                                       8  -0.017  -0.018  1.0359  0.309
                                       9  -0.011  -0.010  1.0983  0.577
                                      10  -0.051  -0.052  2.3982  0.494
                                      11   0.072   0.074  5.0046  0.287
                                      12   0.015   0.014  5.1242  0.401
                                      13  -0.093  -0.093  9.5138  0.147
                                      14  -0.021  -0.024  9.7410  0.204
                                      15  -0.039  -0.032  10.521  0.230
                                      16   0.103   0.100  15.909  0.069
                                      17   0.065   0.066  18.085  0.054
                                      18  -0.053  -0.055  19.513  0.052
                                      19   0.070   0.067  22.054  0.037
                                      20  -0.005   0.003  22.077  0.054
                                      21   0.040   0.044  22.914  0.062
                                      22   0.005  -0.003  22.926  0.086
                                      23   0.058   0.050  24.686  0.076
                                      24   0.007   0.014  24.712  0.101
                                      25  -0.074  -0.065  27.561  0.069
                                      26  -0.040  -0.039  28.417  0.076
                                      27  -0.007  -0.013  28.442  0.099
                                      28   0.037   0.014  29.165  0.110
                                      29   0.016   0.048  29.295  0.137
                                      30  -0.090  -0.089  33.555  0.072
                                      31  -0.091  -0.093  37.893  0.036
                                      32  -0.024  -0.021  38.189  0.044
                                      33   0.008   0.002  38.221  0.058
                                      34  -0.044  -0.038  39.245  0.060
                                      35  -0.051  -0.074  40.657  0.058
                                      36   0.075   0.087  43.684  0.039
```

Figure 12. *Report on winter 2 model for cluster 2 of significant wave heights*

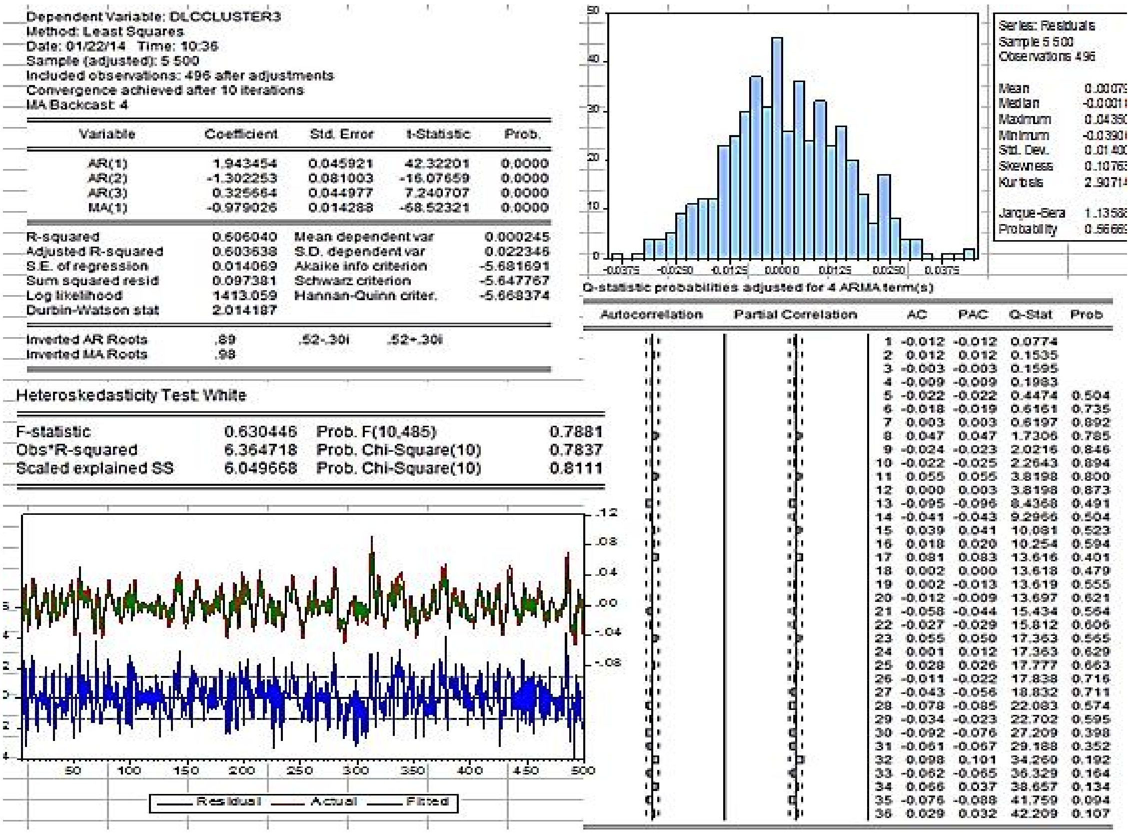


```
Dependent Variable: D(LOG(WHEIGHTCLUSTER3))
Method: Least Squares
Date: 02/18/14   Time: 12:30
Sample: 983 1998
Included observations: 1016
Convergence achieved after 37 iterations
MA Backcast: 974 982

        Variable        Coefficient    Std. Error    t-Statistic    Prob.

          AR(1)          0.449812      0.040319      11.15642      0.0000
          AR(3)         -0.196421      0.026905     -7.300433      0.0000
          AR(5)         -0.049929      0.013687     -3.647877      0.0003
          AR(6)         -0.205934      0.026416     -7.795938      0.0000
          AR(7)          0.091838      0.018054      5.086847      0.0000
          AR(8)          0.793789      0.026342      30.13441      0.0000
          AR(9)         -0.498171      0.038446     -12.95767      0.0000
          MA(1)          0.268838      0.043888      6.125530      0.0000
          MA(3)          0.132680      0.022107      6.001680      0.0000
          MA(6)          0.124970      0.021811      5.729716      0.0000
          MA(8)         -0.857644      0.021396     -40.08436      0.0000
          MA(9)         -0.144801      0.046546     -3.110915      0.0019

R-squared                0.688797    Mean dependent var        0.000114
Adjusted R-squared       0.685387    S.D. dependent var        0.026567
S.E. of regression       0.014902    Akaike info criterion    -5.562937
Sum squared resid        0.222950    Schwarz criterion        -5.504784
Log likelihood           2837.972    Hannan-Quinn criter.     -5.540852
Durbin-Watson stat       2.025029

Inverted AR Roots       .73+.07i      .73-.07i     .71+.71i      .71-.71i
                        .00+1.00i     .00-1.00i    -.72+.65i     -.72-.65i
                          -.98
Inverted MA Roots         .94         .69+.70i     .69-.70i      .00-1.00i
                        .00+1.00i       -.17       -.72+.66i     -.72-.66i
                          -1.00

Heteroskedasticity Test: White

F-statistic              0.905691    Prob. F(78,937)              0.7049
Obs*R-squared            71.22971    Prob. Chi-Square(78)         0.6931
Scaled explained SS      74.07974    Prob. Chi-Square(78)         0.6047
```

```
Series: Residuals
Sample 983 1998
Observations 1016

Mean          0.000184
Median       -0.000662
Maximum       0.057197
Minimum      -0.042218
Std. Dev.     0.014820
Skewness      0.204383
Kurtosis      3.119938

Jarque-Bera   7.682433
Probability   0.021467
```

```
Q-statistic probabilities adjusted for 12 ARMA term(s)

Autocorrelation    Partial Correlation        AC      PAC     Q-Stat   Prob

                                          1 -0.013  -0.013   0.1733
                                          2 -0.008  -0.008   0.2367
                                          3  0.012   0.012   0.3770
                                          4 -0.005  -0.005   0.4044
                                          5  0.015   0.015   0.6236
                                          6 -0.022  -0.022   1.1301
                                          7 -0.005  -0.005   1.1542
                                          8 -0.008  -0.009   1.2208
                                          9 -0.033  -0.033   2.3668
                                         10 -0.010  -0.011   2.4604
                                         11  0.033   0.033   3.5519
                                         12 -0.038  -0.037   5.0206
                                         13  0.040   0.040   6.6743   0.010
                                         14  0.005   0.005   6.6980   0.035
                                         15 -0.054  -0.054   9.6987   0.021
                                         16 -0.012  -0.016   9.8540   0.043
                                         17 -0.040  -0.039   11.507   0.042
                                         18 -0.002  -0.006   11.513   0.074
                                         19  0.003   0.004   11.523   0.117
                                         20 -0.048  -0.044   13.937   0.083
                                         21  0.045   0.041   16.020   0.066
                                         22 -0.014  -0.014   16.232   0.093
                                         23  0.022   0.024   16.723   0.116
                                         24  0.003  -0.007   16.729   0.160
                                         25  0.012   0.014   16.874   0.205
                                         26 -0.032  -0.037   17.933   0.210
                                         27  0.003   0.000   17.941   0.266
                                         28  0.006   0.009   17.984   0.325
                                         29 -0.023  -0.024   18.535   0.356
                                         30  0.035   0.036   19.803   0.344
                                         31 -0.004   0.000   19.820   0.405
                                         32  0.004  -0.006   19.836   0.468
                                         33 -0.038  -0.033   21.333   0.439
                                         34 -0.023  -0.030   21.886   0.467
                                         35  0.044   0.037   23.911   0.409
                                         36  0.013   0.015   24.083   0.457
```

Figure 13. *Report on summer model for cluster 3 of significant wave heights*

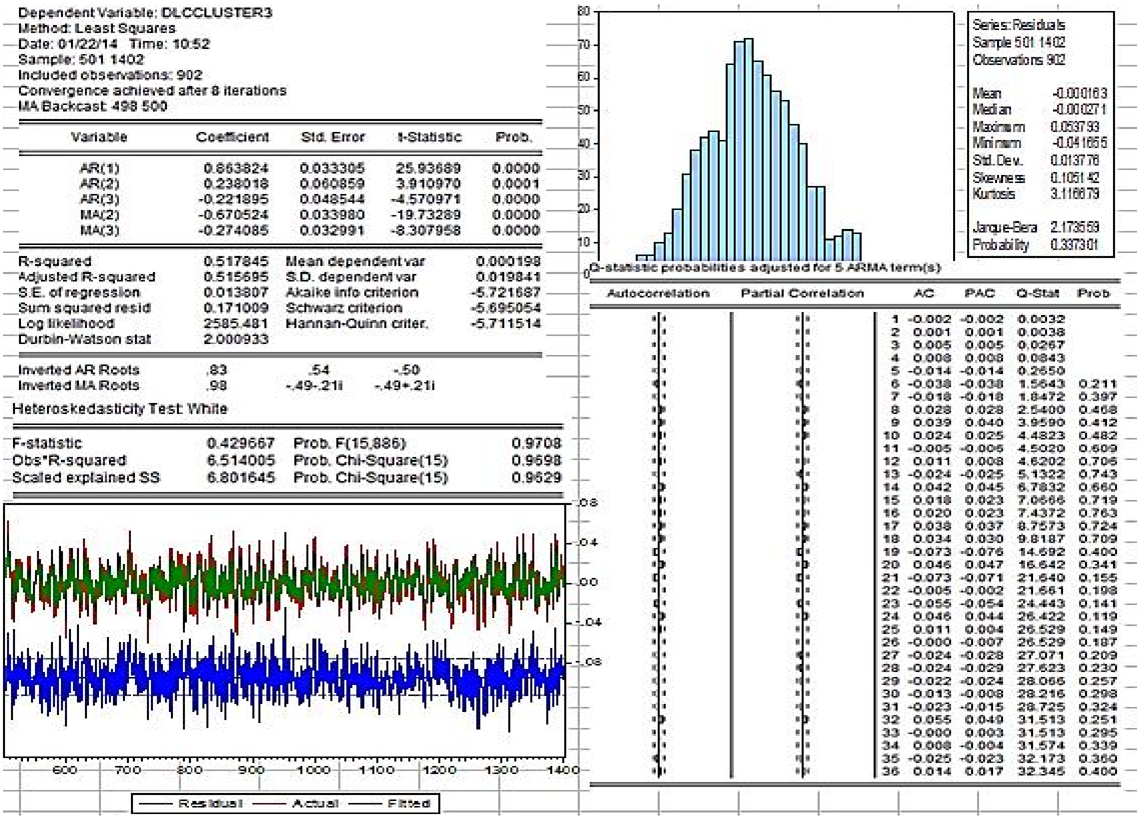


```
Dependent Variable: DLCCLUSTER3
Method: Least Squares
Date: 01/22/14   Time: 10:36
Sample (adjusted): 5 500
Included observations: 496 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 4

        Variable        Coefficient    Std. Error    t-Statistic    Prob.

          AR(1)          1.943454      0.045921      42.32201      0.0000
          AR(2)         -1.302253      0.081003     -16.07659      0.0000
          AR(3)          0.325664      0.044977      7.240707      0.0000
          MA(1)         -0.979026      0.014288     -68.52321      0.0000

R-squared                0.606040    Mean dependent var        0.000245
Adjusted R-squared       0.603638    S.D. dependent var        0.022346
S.E. of regression       0.014069    Akaike info criterion    -5.681691
Sum squared resid        0.097381    Schwarz criterion        -5.647767
Log likelihood           1413.059    Hannan-Quinn criter.     -5.668374
Durbin-Watson stat       2.014187

Inverted AR Roots          .89        .52-.30i      .52+.30i
Inverted MA Roots          .98

Heteroskedasticity Test: White

F-statistic              0.630446    Prob. F(10,485)              0.7881
Obs*R-squared            6.364718    Prob. Chi-Square(10)         0.7837
Scaled explained SS      6.049668    Prob. Chi-Square(10)         0.8111
```

```
Series: Residuals
Sample 5 500
Observations 496

Mean          0.0007
Median       -0.0001
Maximum       0.0435
Minimum      -0.0390
Std. Dev.     0.0140
Skewness      0.1076
Kurtosis      2.9071

Jarque-Bera   1.1358
Probability   0.5666
```

```
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation    Partial Correlation        AC      PAC     Q-Stat   Prob

                                          1 -0.012  -0.012   0.0774
                                          2  0.012   0.012   0.1535
                                          3 -0.003  -0.003   0.1595
                                          4 -0.009  -0.009   0.1983
                                          5 -0.022  -0.022   0.4474   0.504
                                          6 -0.018  -0.019   0.6161   0.735
                                          7  0.003   0.003   0.6197   0.892
                                          8  0.047   0.047   1.7306   0.785
                                          9 -0.024  -0.023   2.0216   0.846
                                         10 -0.022  -0.025   2.2643   0.894
                                         11  0.055   0.055   3.8198   0.800
                                         12  0.000   0.003   3.8198   0.873
                                         13 -0.095  -0.096   8.4368   0.491
                                         14 -0.041  -0.043   9.2966   0.504
                                         15  0.039   0.041   10.081   0.523
                                         16  0.018   0.020   10.254   0.594
                                         17  0.081   0.083   13.616   0.401
                                         18  0.002   0.000   13.618   0.479
                                         19  0.002  -0.013   13.619   0.555
                                         20 -0.012  -0.009   13.697   0.621
                                         21 -0.058  -0.044   15.434   0.564
                                         22 -0.027  -0.029   15.812   0.606
                                         23  0.055   0.050   17.363   0.565
                                         24  0.001   0.012   17.363   0.629
                                         25  0.028   0.026   17.777   0.663
                                         26 -0.011  -0.022   17.838   0.716
                                         27 -0.043  -0.056   18.832   0.711
                                         28 -0.078  -0.085   22.083   0.574
                                         29 -0.034  -0.023   22.702   0.595
                                         30 -0.092  -0.076   27.209   0.398
                                         31 -0.061  -0.067   29.188   0.352
                                         32  0.098   0.101   34.260   0.192
                                         33 -0.062  -0.065   36.329   0.164
                                         34  0.066   0.037   38.657   0.134
                                         35 -0.076  -0.088   41.759   0.094
                                         36  0.029   0.032   42.209   0.107
```

Figure 14. *Report on winter 1 model for cluster 3 of significant wave heights*

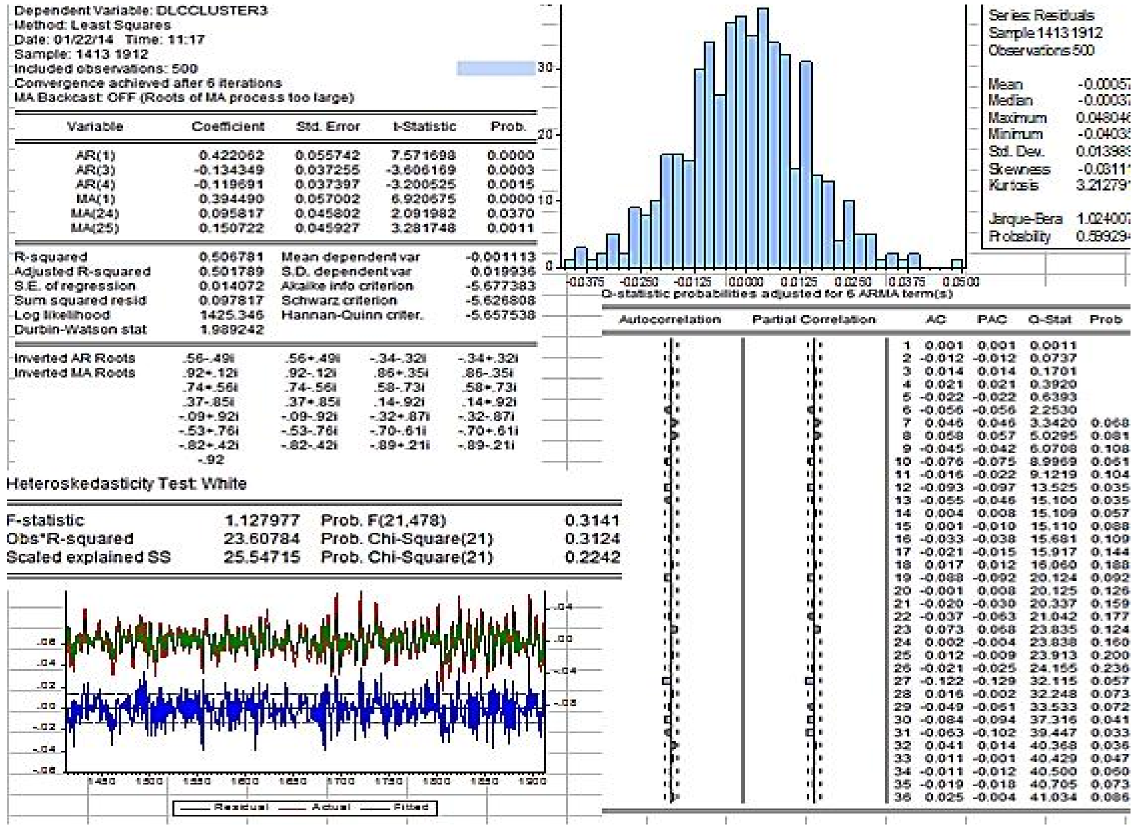


```
Dependent Variable: DLCCLUSTER3
Method: Least Squares
Date: 01/22/14   Time: 10:52
Sample: 501 1402
Included observations: 902
Convergence achieved after 8 iterations
MA Backcast: 498 500

      Variable        Coefficient    Std. Error    t-Statistic    Prob.

        AR(1)          0.863824      0.033305      25.93689      0.0000
        AR(2)          0.238018      0.060859      3.910970      0.0001
        AR(3)         -0.221895      0.048544     -4.570971      0.0000
        MA(2)         -0.670524      0.033980     -19.73289      0.0000
        MA(3)         -0.274085      0.032991     -8.307958      0.0000

R-squared               0.517845   Mean dependent var       0.000198
Adjusted R-squared      0.515695   S.D. dependent var       0.019841
S.E. of regression      0.013807   Akaike info criterion   -5.721687
Sum squared resid       0.171009   Schwarz criterion       -5.695054
Log likelihood          2585.481   Hannan-Quinn criter.    -5.711514
Durbin-Watson stat      2.000933

Inverted AR Roots         .83          .54          -.50
Inverted MA Roots         .98      -.49-.21i    -.49+.21i

Heteroskedasticity Test: White

F-statistic              0.429667   Prob. F(15,886)              0.9708
Obs*R-squared            6.514005   Prob. Chi-Square(15)         0.9698
Scaled explained SS      6.801645   Prob. Chi-Square(15)         0.9629
```

```
Series: Residuals
Sample 501 1402
Observations 902

Mean         -0.000163
Median       -0.000271
Maximum       0.053793
Minimum      -0.041655
Std. Dev.     0.013776
Skewness      0.105142
Kurtosis      3.116679

Jarque-Bera   2.173559
Probability   0.337301
```

```
Q-statistic probabilities adjusted for 5 ARMA term(s)

Autocorrelation   Partial Correlation       AC     PAC    Q-Stat   Prob

                                      1  -0.002  -0.002   0.0032
                                      2   0.001   0.001   0.0038
                                      3   0.005   0.005   0.0267
                                      4   0.008   0.008   0.0843
                                      5  -0.014  -0.014   0.2650
                                      6  -0.038  -0.038   1.5643   0.211
                                      7  -0.018  -0.018   1.8472   0.397
                                      8   0.028   0.028   2.5400   0.468
                                      9   0.039   0.040   3.9590   0.412
                                     10   0.024   0.025   4.4823   0.482
                                     11  -0.005  -0.006   4.5020   0.609
                                     12   0.011   0.008   4.6202   0.706
                                     13  -0.024  -0.025   5.1322   0.743
                                     14   0.042   0.045   6.7832   0.660
                                     15   0.018   0.023   7.0666   0.719
                                     16   0.020   0.023   7.4372   0.763
                                     17   0.038   0.037   8.7573   0.724
                                     18   0.034   0.030   9.8187   0.709
                                     19  -0.073  -0.076   14.692   0.400
                                     20   0.046   0.047   16.642   0.341
                                     21  -0.073  -0.071   21.640   0.155
                                     22  -0.005  -0.002   21.661   0.198
                                     23  -0.055  -0.054   24.443   0.141
                                     24   0.046   0.044   26.422   0.119
                                     25   0.011   0.004   26.529   0.149
                                     26  -0.000  -0.007   26.529   0.187
                                     27  -0.024  -0.028   27.071   0.209
                                     28  -0.024  -0.029   27.623   0.230
                                     29  -0.022  -0.024   28.066   0.257
                                     30  -0.013  -0.008   28.216   0.298
                                     31  -0.023  -0.015   28.725   0.324
                                     32   0.055   0.049   31.513   0.251
                                     33  -0.000   0.003   31.513   0.295
                                     34   0.008  -0.004   31.574   0.339
                                     35  -0.025  -0.023   32.173   0.360
                                     36   0.014   0.017   32.345   0.400
```

Figure 15. *Report on winter 2 model for cluster 3 of significant wave heights*

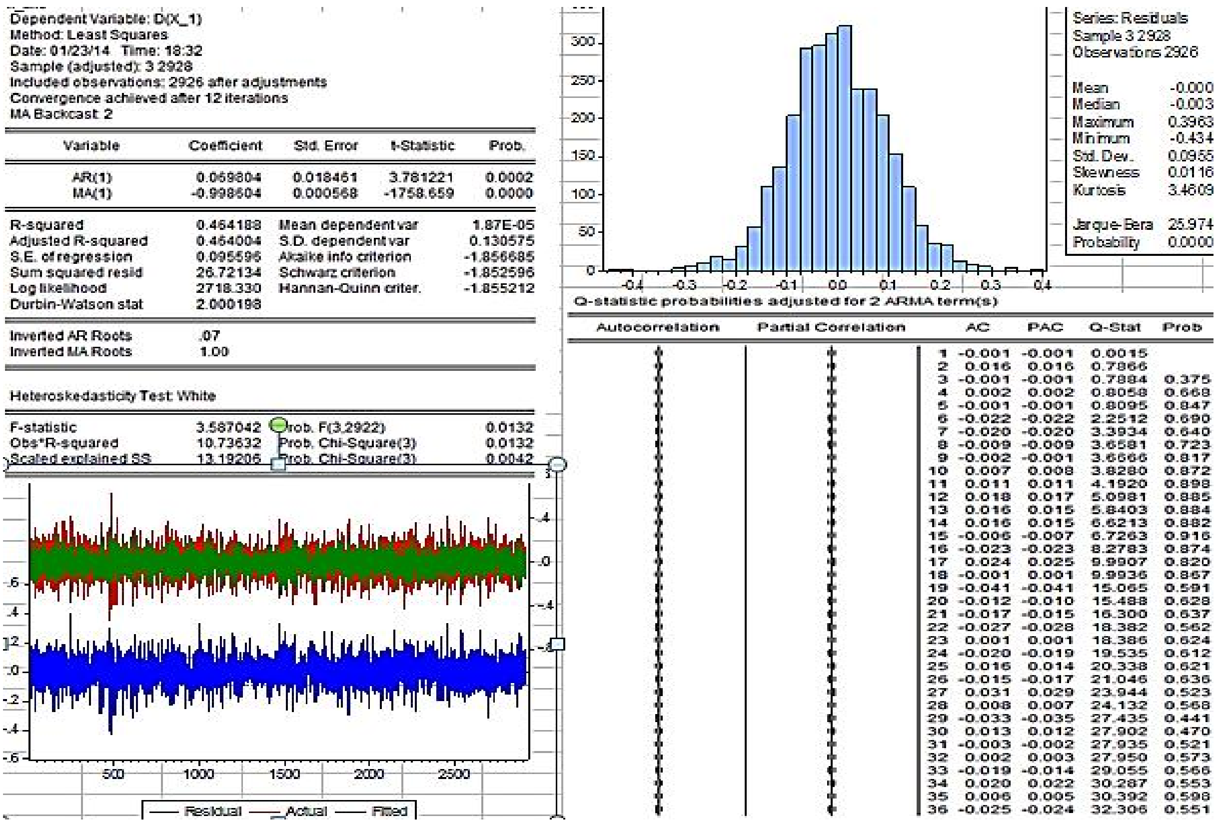


```
Dependent Variable: DLCCLUSTER3
Method: Least Squares
Date: 01/22/14   Time: 11:17
Sample: 1413 1912
Included observations: 500
Convergence achieved after 6 iterations
MA Backcast: OFF (Roots of MA process too large)

      Variable        Coefficient    Std. Error    t-Statistic    Prob.

        AR(1)          0.422062      0.055742      7.571698      0.0000
        AR(3)         -0.134349      0.037255     -3.606169      0.0003
        AR(4)         -0.119691      0.037397     -3.200525      0.0015
        MA(1)          0.394490      0.057002      6.920675      0.0000
        MA(24)         0.095817      0.045802      2.091982      0.0370
        MA(25)         0.150722      0.045927      3.281748      0.0011

R-squared               0.506781   Mean dependent var      -0.001113
Adjusted R-squared      0.501789   S.D. dependent var       0.019936
S.E. of regression      0.014072   Akaike info criterion   -5.677383
Sum squared resid       0.097817   Schwarz criterion       -5.626808
Log likelihood          1425.346   Hannan-Quinn criter.    -5.657538
Durbin-Watson stat      1.989242

Inverted AR Roots      .56-.49i     .56+.49i    -.34-.32i    -.34+.32i
Inverted MA Roots      .92+.12i     .92-.12i     .86+.35i     .86-.35i
                       .74+.56i     .74-.56i     .58-.73i     .58+.73i
                       .37-.85i     .37+.85i     .14-.92i     .14+.92i
                      -.09+.92i    -.09-.92i    -.32+.87i    -.32-.87i
                      -.53+.76i    -.53-.76i    -.70-.61i    -.70+.61i
                      -.82+.42i    -.82-.42i    -.89+.21i    -.89-.21i
                        -.92

Heteroskedasticity Test: White

F-statistic              1.127977   Prob. F(21,478)              0.3141
Obs*R-squared            23.60784   Prob. Chi-Square(21)         0.3124
Scaled explained SS      25.54715   Prob. Chi-Square(21)         0.2242
```

```
Series: Residuals
Sample 1413 1912
Observations 500

Mean         -0.00057
Median       -0.00037
Maximum       0.048046
Minimum      -0.04035
Std. Dev.     0.013989
Skewness     -0.03111
Kurtosis      3.21279

Jarque-Bera   1.024007
Probability   0.58929
```

```
Q-statistic probabilities adjusted for 6 ARMA term(s)

Autocorrelation   Partial Correlation       AC     PAC    Q-Stat   Prob

                                      1   0.001   0.001   0.0011
                                      2  -0.012  -0.012   0.0737
                                      3   0.014   0.014   0.1701
                                      4   0.021   0.021   0.3920
                                      5  -0.022  -0.022   0.6393
                                      6  -0.056  -0.056   2.2530
                                      7   0.046   0.046   3.3420   0.068
                                      8   0.058   0.057   5.0295   0.081
                                      9  -0.045  -0.042   6.0708   0.108
                                     10  -0.076  -0.075   8.9969   0.061
                                     11  -0.016  -0.022   9.1219   0.104
                                     12  -0.093  -0.097   13.525   0.035
                                     13  -0.055  -0.046   15.100   0.035
                                     14   0.004   0.008   15.109   0.057
                                     15   0.001  -0.010   15.110   0.088
                                     16  -0.033  -0.038   15.681   0.109
                                     17  -0.021  -0.015   15.917   0.144
                                     18   0.017   0.012   16.060   0.188
                                     19  -0.088  -0.092   20.124   0.092
                                     20  -0.001   0.008   20.125   0.126
                                     21  -0.020  -0.030   20.337   0.159
                                     22  -0.037  -0.063   21.042   0.177
                                     23   0.073   0.068   23.835   0.124
                                     24   0.002  -0.004   23.838   0.160
                                     25   0.012  -0.009   23.913   0.200
                                     26  -0.021  -0.025   24.155   0.236
                                     27  -0.122  -0.129   32.115   0.057
                                     28   0.016  -0.002   32.248   0.073
                                     29  -0.049  -0.061   33.533   0.072
                                     30  -0.084  -0.094   37.316   0.041
                                     31  -0.063  -0.102   39.447   0.033
                                     32   0.041   0.014   40.368   0.036
                                     33   0.011  -0.001   40.429   0.047
                                     34  -0.011  -0.012   40.500   0.060
                                     35  -0.019  -0.018   40.705   0.073
                                     36   0.025  -0.004   41.034   0.086
```

Figure 16. *Report on winter 3 model for cluster 3 of significant wave heights*

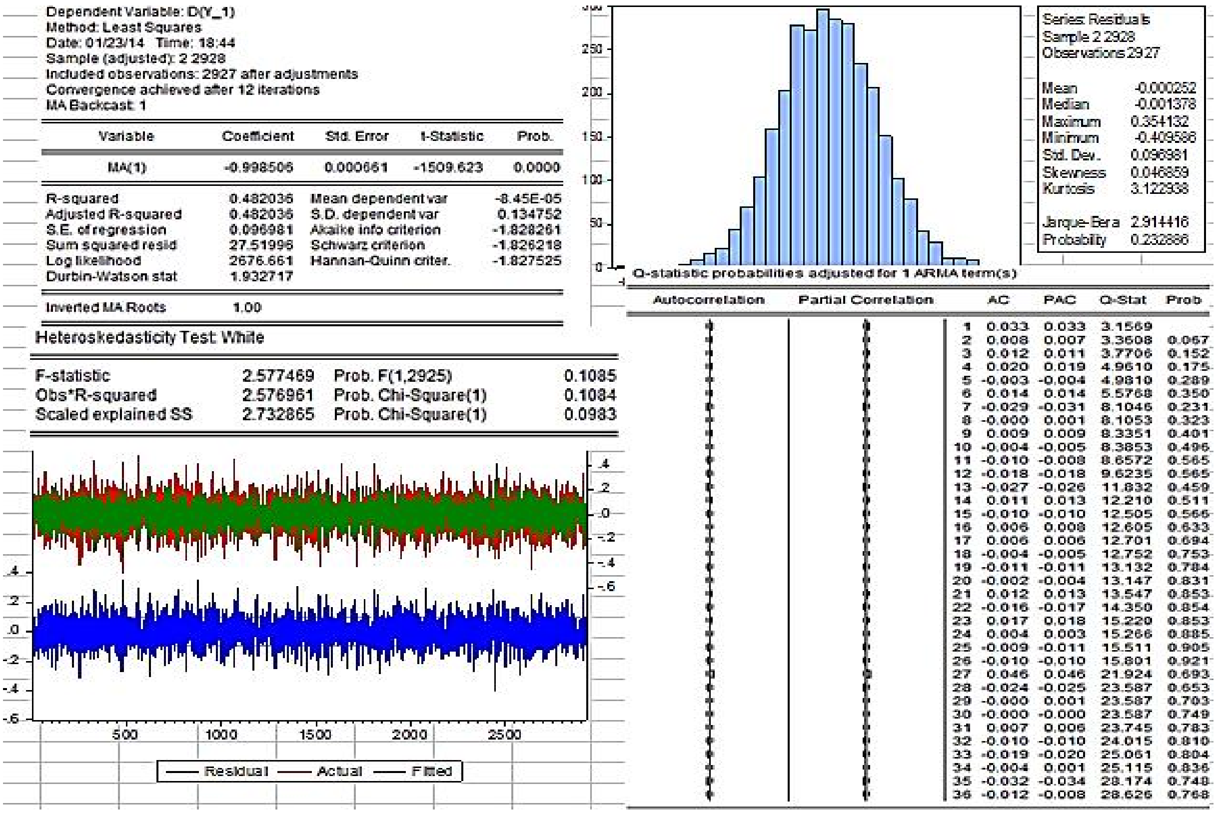


```
Dependent Variable: D(X_1)
Method: Least Squares
Date: 01/23/14   Time: 18:32
Sample (adjusted): 3 2928
Included observations: 2926 after adjustments
Convergence achieved after 12 iterations
MA Backcast: 2

     Variable        Coefficient    Std. Error    t-Statistic     Prob.

       AR(1)           0.069804      0.018461      3.781221      0.0002
       MA(1)          -0.998604      0.000568     -1758.659      0.0000

R-squared              0.464188   Mean dependent var      1.87E-05
Adjusted R-squared     0.464004   S.D. dependent var      0.130575
S.E. of regression     0.095596   Akaike info criterion  -1.856685
Sum squared resid      26.72134   Schwarz criterion      -1.852596
Log likelihood         2718.330   Hannan-Quinn criter.   -1.855212
Durbin-Watson stat     2.000198

Inverted AR Roots       .07
Inverted MA Roots       1.00

Heteroskedasticity Test: White

F-statistic            3.587042   Prob. F(3,2922)            0.0132
Obs*R-squared          10.73632   Prob. Chi-Square(3)        0.0132
Scaled explained SS    13.19206   Prob. Chi-Square(3)        0.0042
```

```
Series: Residuals
Sample 3 2928
Observations 2926

Mean         -0.000
Median       -0.003
Maximum       0.3963
Minimum      -0.434
Std. Dev.     0.0955
Skewness      0.0116
Kurtosis      3.4609

Jarque-Bera   25.974
Probability   0.0000
```

```
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation   Partial Correlation       AC      PAC     Q-Stat   Prob

                                        1 -0.001  -0.001   0.0015
                                        2  0.016   0.016   0.7866
                                        3 -0.001  -0.001   0.7884   0.375
                                        4  0.002   0.002   0.8058   0.668
                                        5 -0.001  -0.001   0.8095   0.847
                                        6 -0.022  -0.022   2.2512   0.690
                                        7 -0.020  -0.020   3.3934   0.640
                                        8 -0.009  -0.009   3.6581   0.723
                                        9 -0.002  -0.001   3.6666   0.817
                                       10  0.007   0.008   3.8280   0.872
                                       11  0.011   0.011   4.1920   0.898
                                       12  0.018   0.017   5.0981   0.885
                                       13  0.016   0.015   5.8403   0.884
                                       14  0.016   0.015   6.6213   0.882
                                       15 -0.006  -0.007   6.7263   0.916
                                       16 -0.023  -0.023   8.2783   0.874
                                       17  0.024   0.025   9.9907   0.820
                                       18 -0.001   0.001   9.9936   0.867
                                       19 -0.041  -0.041   15.065   0.591
                                       20 -0.012  -0.010   15.488   0.628
                                       21 -0.017  -0.015   16.300   0.637
                                       22 -0.027  -0.028   18.382   0.562
                                       23  0.001   0.001   18.386   0.624
                                       24 -0.020  -0.019   19.535   0.612
                                       25  0.016   0.014   20.338   0.621
                                       26 -0.015  -0.017   21.046   0.636
                                       27  0.031   0.029   23.944   0.523
                                       28  0.008   0.007   24.132   0.568
                                       29 -0.033  -0.035   27.435   0.441
                                       30  0.013   0.012   27.902   0.470
                                       31 -0.003  -0.002   27.935   0.521
                                       32  0.002   0.003   27.950   0.573
                                       33 -0.019  -0.014   29.055   0.566
                                       34  0.020   0.022   30.287   0.553
                                       35  0.006   0.005   30.392   0.598
                                       36 -0.025  -0.024   32.306   0.551
```

Figure 17. *Report on X axe model for cluster 1 of wave directions*

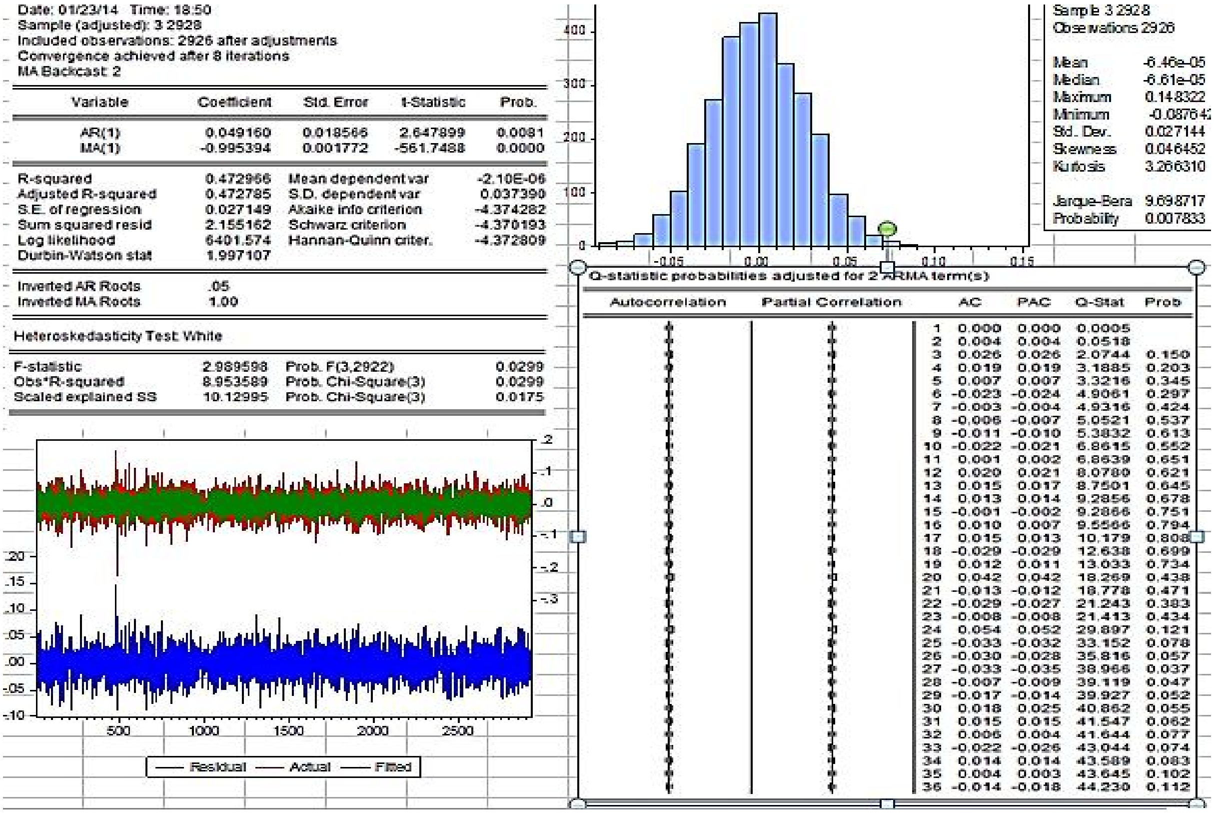


```
Dependent Variable: D(Y_1)
Method: Least Squares
Date: 01/23/14   Time: 18:44
Sample (adjusted): 2 2928
Included observations: 2927 after adjustments
Convergence achieved after 12 iterations
MA Backcast: 1

     Variable        Coefficient    Std. Error    t-Statistic     Prob.

       MA(1)          -0.998506      0.000661     -1509.623      0.0000

R-squared              0.482036   Mean dependent var     -8.45E-05
Adjusted R-squared     0.482036   S.D. dependent var      0.134752
S.E. of regression     0.096981   Akaike info criterion  -1.828261
Sum squared resid      27.51996   Schwarz criterion      -1.826218
Log likelihood         2676.661   Hannan-Quinn criter.   -1.827525
Durbin-Watson stat     1.932717

Inverted MA Roots       1.00

Heteroskedasticity Test: White

F-statistic            2.577469   Prob. F(1,2925)            0.1085
Obs*R-squared          2.576961   Prob. Chi-Square(1)        0.1084
Scaled explained SS    2.732865   Prob. Chi-Square(1)        0.0983
```

```
Series: Residuals
Sample 2 2928
Observations 2927

Mean         -0.000252
Median       -0.001378
Maximum       0.354132
Minimum      -0.409586
Std. Dev.     0.096981
Skewness      0.046859
Kurtosis      3.122938

Jarque-Bera   2.914416
Probability   0.232886
```

```
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation   Partial Correlation       AC      PAC     Q-Stat   Prob

                                        1  0.033   0.033   3.1569
                                        2  0.008   0.007   3.3608   0.067
                                        3  0.012   0.011   3.7706   0.152
                                        4  0.020   0.019   4.9610   0.175
                                        5 -0.003  -0.004   4.9810   0.289
                                        6  0.014   0.014   5.5768   0.350
                                        7 -0.029  -0.031   8.1046   0.231
                                        8 -0.000   0.001   8.1053   0.323
                                        9  0.009   0.009   8.3351   0.401
                                       10 -0.004  -0.005   8.3853   0.496
                                       11 -0.010  -0.008   8.6572   0.565
                                       12 -0.018  -0.018   9.6235   0.565
                                       13 -0.027  -0.026   11.832   0.459
                                       14  0.011   0.013   12.210   0.511
                                       15 -0.010  -0.010   12.505   0.566
                                       16  0.006   0.008   12.605   0.633
                                       17  0.006   0.006   12.701   0.694
                                       18 -0.004  -0.005   12.752   0.753
                                       19 -0.011  -0.011   13.132   0.784
                                       20 -0.002  -0.004   13.147   0.831
                                       21  0.012   0.013   13.547   0.853
                                       22 -0.016  -0.017   14.350   0.854
                                       23  0.017   0.018   15.220   0.853
                                       24  0.004   0.003   15.266   0.885
                                       25 -0.009  -0.011   15.511   0.905
                                       26 -0.010  -0.010   15.801   0.921
                                       27  0.046   0.046   21.924   0.693
                                       28 -0.024  -0.025   23.587   0.653
                                       29 -0.000   0.001   23.587   0.703
                                       30 -0.000  -0.000   23.587   0.749
                                       31  0.007   0.006   23.745   0.783
                                       32 -0.010  -0.010   24.015   0.810
                                       33 -0.019  -0.020   25.061   0.804
                                       34 -0.004   0.001   25.115   0.836
                                       35 -0.032  -0.034   28.174   0.748
                                       36 -0.012  -0.008   28.626   0.768
```

Figure 18. *Report on Y axe model for cluster 1 of wave directions*

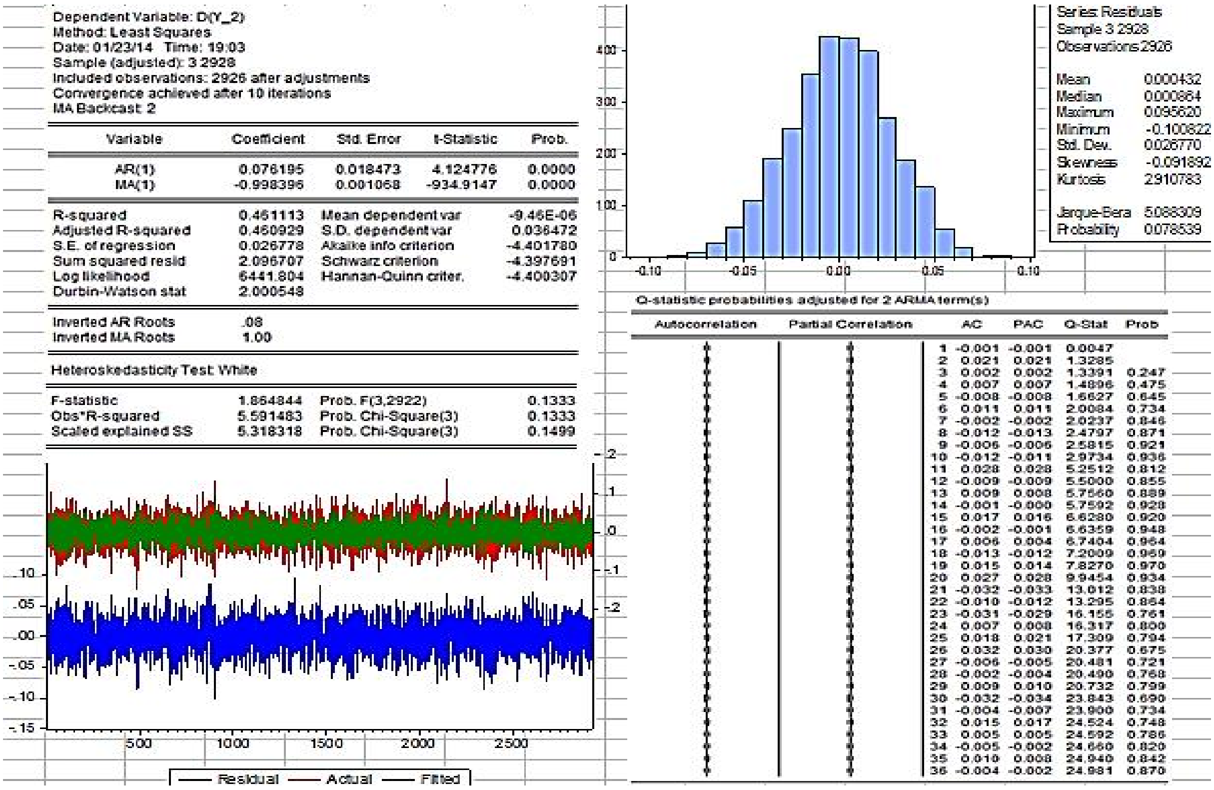


```
Date: 01/23/14   Time: 18:50
Sample (adjusted): 3 2928
Included observations: 2926 after adjustments
Convergence achieved after 8 iterations
MA Backcast: 2

Variable        Coefficient    Std. Error    t-Statistic    Prob.

AR(1)           0.049160       0.018566      2.647899       0.0081
MA(1)          -0.995394       0.001772     -561.7488       0.0000

R-squared               0.472966    Mean dependent var       -2.10E-06
Adjusted R-squared      0.472785    S.D. dependent var        0.037390
S.E. of regression      0.027149    Akaike info criterion    -4.374282
Sum squared resid       2.155162    Schwarz criterion        -4.370193
Log likelihood          6401.574    Hannan-Quinn criter.     -4.372809
Durbin-Watson stat      1.997107

Inverted AR Roots       .05
Inverted MA Roots       1.00

Heteroskedasticity Test: White

F-statistic             2.989598    Prob. F(3,2922)           0.0299
Obs*R-squared           8.953589    Prob. Chi-Square(3)       0.0299
Scaled explained SS     10.12995    Prob. Chi-Square(3)       0.0175
```

```
Sample 3 2928
Observations 2926

Mean          -6.46e-05
Median        -6.61e-05
Maximum        0.148322
Minimum       -0.08764
Std. Dev.      0.027144
Skewness       0.046452
Kurtosis       3.266310

Jarque-Bera    9.698717
Probability    0.007833
```

```
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation   Partial Correlation      AC     PAC    Q-Stat   Prob

                                     1  0.000  0.000  0.0005
                                     2  0.004  0.004  0.0518
                                     3  0.026  0.026  2.0744   0.150
                                     4  0.019  0.019  3.1885   0.203
                                     5  0.007  0.007  3.3216   0.345
                                     6 -0.023 -0.024  4.9061   0.297
                                     7 -0.003 -0.004  4.9316   0.424
                                     8 -0.006 -0.007  5.0521   0.537
                                     9 -0.011 -0.010  5.3832   0.613
                                    10 -0.022 -0.021  6.8615   0.552
                                    11  0.001  0.002  6.8639   0.651
                                    12  0.020  0.021  8.0780   0.621
                                    13  0.015  0.017  8.7501   0.645
                                    14  0.013  0.014  9.2856   0.678
                                    15 -0.001 -0.002  9.2866   0.751
                                    16  0.010  0.007  9.5566   0.794
                                    17  0.015  0.013  10.179   0.808
                                    18 -0.029 -0.029  12.638   0.699
                                    19  0.012  0.011  13.033   0.734
                                    20  0.042  0.042  18.269   0.438
                                    21 -0.013 -0.012  18.778   0.471
                                    22 -0.029 -0.027  21.243   0.383
                                    23 -0.008 -0.008  21.413   0.434
                                    24  0.054  0.052  29.897   0.121
                                    25 -0.033 -0.032  33.152   0.078
                                    26 -0.030 -0.028  35.816   0.057
                                    27 -0.033 -0.035  38.966   0.037
                                    28 -0.007 -0.009  39.119   0.047
                                    29 -0.017 -0.014  39.927   0.052
                                    30  0.018  0.025  40.862   0.055
                                    31  0.015  0.015  41.547   0.062
                                    32  0.006  0.004  41.644   0.077
                                    33 -0.022 -0.026  43.044   0.074
                                    34  0.014  0.014  43.589   0.083
                                    35  0.004  0.003  43.645   0.102
                                    36 -0.014 -0.018  44.230   0.112
```

Figure 19. *Report on X axe model for cluster 2 of wave directions*



```
Dependent Variable: D(Y_2)
Method: Least Squares
Date: 01/23/14   Time: 19:03
Sample (adjusted): 3 2928
Included observations: 2926 after adjustments
Convergence achieved after 10 iterations
MA Backcast: 2

Variable        Coefficient    Std. Error    t-Statistic    Prob.

AR(1)           0.076195       0.018473      4.124776       0.0000
MA(1)          -0.998396       0.001068     -934.9147       0.0000

R-squared               0.461113    Mean dependent var       -9.46E-06
Adjusted R-squared      0.460929    S.D. dependent var        0.036472
S.E. of regression      0.026778    Akaike info criterion    -4.401780
Sum squared resid       2.096707    Schwarz criterion        -4.397691
Log likelihood          6441.804    Hannan-Quinn criter.     -4.400307
Durbin-Watson stat      2.000548

Inverted AR Roots       .08
Inverted MA Roots       1.00

Heteroskedasticity Test: White

F-statistic             1.864844    Prob. F(3,2922)           0.1333
Obs*R-squared           5.591483    Prob. Chi-Square(3)       0.1333
Scaled explained SS     5.318318    Prob. Chi-Square(3)       0.1499
```

```
Series: Residuals
Sample 3 2928
Observations 2926

Mean           0.000432
Median         0.000864
Maximum        0.095620
Minimum       -0.100822
Std. Dev.      0.026770
Skewness      -0.091892
Kurtosis       2.910783

Jarque-Bera    5.088309
Probability    0.078539
```

```
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation   Partial Correlation      AC     PAC    Q-Stat   Prob

                                     1 -0.001 -0.001  0.0047
                                     2  0.021  0.021  1.3285
                                     3  0.002  0.002  1.3391   0.247
                                     4  0.007  0.007  1.4896   0.475
                                     5 -0.008 -0.008  1.6627   0.645
                                     6  0.011  0.011  2.0084   0.734
                                     7 -0.002 -0.002  2.0237   0.846
                                     8 -0.012 -0.013  2.4797   0.871
                                     9 -0.006 -0.006  2.5815   0.921
                                    10 -0.012 -0.011  2.9734   0.936
                                    11  0.028  0.028  5.2512   0.812
                                    12 -0.009 -0.009  5.5000   0.855
                                    13  0.009  0.008  5.7560   0.889
                                    14 -0.001 -0.000  5.7592   0.928
                                    15  0.017  0.016  6.6280   0.920
                                    16 -0.002 -0.001  6.6359   0.948
                                    17  0.006  0.004  6.7404   0.964
                                    18 -0.013 -0.012  7.2009   0.969
                                    19  0.015  0.014  7.8270   0.970
                                    20  0.027  0.028  9.9454   0.934
                                    21 -0.032 -0.033  13.012   0.838
                                    22 -0.010 -0.012  13.295   0.864
                                    23 -0.031 -0.029  16.155   0.761
                                    24  0.007  0.008  16.317   0.800
                                    25  0.018  0.021  17.309   0.794
                                    26  0.032  0.030  20.377   0.675
                                    27 -0.006 -0.005  20.481   0.721
                                    28 -0.002 -0.004  20.490   0.768
                                    29  0.009  0.010  20.732   0.799
                                    30 -0.032 -0.034  23.843   0.690
                                    31 -0.004 -0.007  23.900   0.734
                                    32  0.015  0.017  24.524   0.748
                                    33  0.005  0.005  24.592   0.786
                                    34 -0.005 -0.002  24.660   0.820
                                    35  0.010  0.008  24.940   0.842
                                    36 -0.004 -0.002  24.981   0.870
```

Figure 20. *Report on Y axe model for cluster 2 of wave directions*

As one can see, the models above are adequate and ready to be used for both simulation and forecasting, which, in turn, will be described in detail in the ongoing chapters.

Param.	Cl_ID	Season	Start_Hour_Id	Fin_Hour_Id	Start_Day	Fin_Day
SWH	1	winter 1	0	471	01.01.2014	28.02.2014
SWH	1	winter 2	472	982	01.03.2014	03.05.2014
SWH	1	summer	983	1998	03.05.2014	07.09.2014
SWH	1	winter 1	1999	2927	07.09.2014	01.01.2015
SWH	2	summer	983	1998	03.05.2014	07.09.2014
SWH	2	winter 1	1999	2927	07.09.2014	01.01.2015
SWH	2	winter 1	0	477	01.01.2014	01.03.2014
SWH	2	winter 2	478	982	01.03.2014	03.05.2014
SWH	3	summer	983	1998	03.05.2014	07.09.2014
SWH	3	winter 3	1999	2495	07.09.2014	08.11.2014
SWH	3	winter 1	2496	2927	09.11.2014	01.01.2015
SWH	3	winter 1	0	471	01.01.2014	28.02.2014
SWH	3	winter 2	472	982	01.03.2014	03.05.2014
WDX	1	-	0	2927	01.01.2014	01.01.2015
WDX	2	-	0	2927	01.01.2014	01.01.2015
WDY	1	-	0	2927	01.01.2014	01.01.2015
WDY	2	-	0	2927	01.01.2014	01.01.2015

Table 6. *Relevant dates and models Table*

After the analysis of models for aggregated over the years data, described in paragraph 7.5, we found that this aggregation had led to a significant loss of variability of the modelled parameters, which on one hand let us build statistically significant models but on the other hand became a matter of concern for the professionals, that build such schedules for oil companies. Thus, they suggested that we use real-like (non-aggregated over years) time series processes in simulation rather than time series of aggregated data, even if these models are less adequate from the statistical point of view and are not that stable in the long-term run due to poor handling of data variability imposed by standard econometric models applied.

Data to be analyzed in such a case has been transformed in the following way: first choice of clusters' representatives has been carried out by means of rule (4.7.5) in order to use the data closest to the centroids of the corresponding clusters.

$$\overset{\frown}{w}_{c,y,m,d,h,t} = \underset{w_{i,y,m,d,h,t}}{\arg\min} \left(\left\| w_{i,y,m,d,h,t} - \frac{1}{\| c \|} \sum_{i \in c} w_{i,y,m,d,h,t} \right\|^2 \right), c \in C \, , \tag{4.7.5}$$

where $w_{i,y,m,d,h,t}$ is an observation from original time series, C = $\{c_1, c_2, \ldots, c_n\}$ - is a set of clusters for the corresponding time series, y, m, d, h are correspondingly year, month, day and hour of an observation, $t \in \{SWH, WD_x, WD_y\}$, $\|\bullet\|$ is a measure defined in section 7.3. Aggregated time series have been afterwards tested upon stationarity and occurred to be I(1) in accordance with Augmented Dickey-Fuller test. For the reasons described in paragraph 7.5, which remain actual for this sort of data, transformation (4.7.6) has been applied to wave directions data and cluster 3 of SWH data.

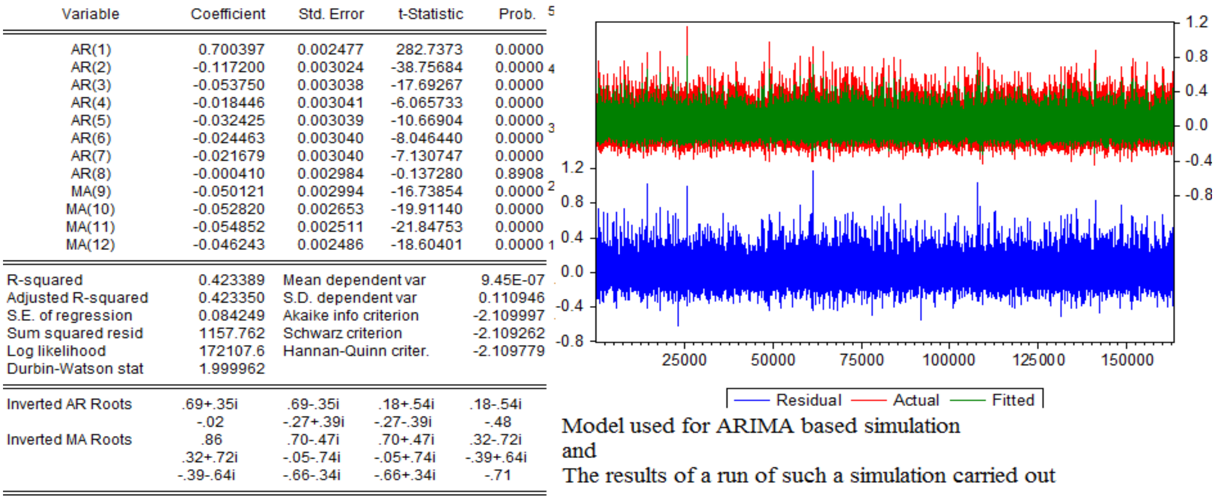
$$\bar{d}_{c,m,d,h,t} = \tilde{w}_{c,m,d,h+3,t} - \tilde{w}_{c,m,d,h,t}\,, \tag{4.7.6}$$

whereas for clusters 1 and 2 of significant wave heights data transformation (4.7.7) has been made:

$$\bar{v}_{c,m,d,h,t} = \ln\left(\frac{\tilde{w}_{c,m,d,h+3,t}}{\tilde{w}_{c,m,d,h,t}}\right). \tag{4.7.7}$$

Afterwards ARIMA based statistical models were addressed. Models for each cluster of each weather parameter were built for the data closest to the centroids of the corresponding clusters so as to leave as much variability of the data as possible. The constructed models are considered to be relevant for the whole cluster they belong.

Time series, closest to the centroid of cluster 1 of SWH is wheight1_nora10_5934n_02 time series, thus the corresponding ARIMA model is addressed for simulation, and this model looks as follows:



```
        Variable          Coefficient    Std. Error    t-Statistic      Prob.
=============================================================================
          AR(1)             0.700397      0.002477      282.7373       0.0000
          AR(2)            -0.117200      0.003024     -38.75684       0.0000
          AR(3)            -0.053750      0.003038     -17.69267       0.0000
          AR(4)            -0.018446      0.003041     -6.065733       0.0000
          AR(5)            -0.032425      0.003039     -10.66904       0.0000
          AR(6)            -0.024463      0.003040     -8.046440       0.0000
          AR(7)            -0.021679      0.003040     -7.130747       0.0000
          AR(8)            -0.000410      0.002984     -0.137280       0.8908
          MA(9)            -0.050121      0.002994     -16.73854       0.0000
          MA(10)           -0.052820      0.002653     -19.91140       0.0000
          MA(11)           -0.054852      0.002511     -21.84753       0.0000
          MA(12)           -0.046243      0.002486     -18.60401       0.0000
=============================================================================
R-squared                   0.423389    Mean dependent var          9.45E-07
Adjusted R-squared          0.423350    S.D. dependent var          0.110946
S.E. of regression          0.084249    Akaike info criterion      -2.109997
Sum squared resid           1157.762    Schwarz criterion          -2.109262
Log likelihood              172107.6    Hannan-Quinn criter.       -2.109779
Durbin-Watson stat          1.999962
=============================================================================
Inverted AR Roots          .69+.35i      .69-.35i      .18+.54i      .18-.54i
                             -.02       -.27+.39i     -.27-.39i        -.48
Inverted MA Roots             .86        .70-.47i      .70+.47i      .32-.72i
                           .32+.72i     -.05-.74i     -.05+.74i     -.39+.64i
                          -.39-.64i     -.66-.34i     -.66+.34i        -.71
=============================================================================
```

Model used for ARIMA based simulation
and
The results of a run of such a simulation carried out

Figure 21. *Report on model for cluster 1 of non-aggregated significant wave heights*

As one can see coefficients of the independent variables of the model are all significant and the adjusted R-squared is high enough, meaning that more than 42% of the variability of the dependent variable is explained by the variability of independent variables. Unfortunately high variability of data did not let us built a statistically significant model (for forecasts) as those, represented in the previous paragraphs, since the residuals of such a model are not normally distributed and have significant (however extremely small in absolute values) autocorrelations. We have tried several methodologies such as ARCH-GARCH modelling of the residuals, different sorts of data transformations and infiltrations to deal with high variability of data; however nothing provided us with a significantly better model, though usage of GARCH(1,1) model helped to slightly decrease significance of the autocorrelations of the residuals. Since we have not found a better alternative a model shown in Figure 21 was considered to be the best alternative for being addressed for simulation of individual time series of SWH. Note that in series of experiments, example of which is presented in Figure 21, it is shown that such models might be used for short runs of the simulation, though the system might become unstable in long term cases; unacceptable instances of the simulation exceeding the accurately chosen confidence intervals must be infiltrated. Nevertheless it should be noted that ARIMA modelling of **non-aggregated** time series of significant wave heights in long term runs still remains an unresolved task and might well represent a challenge for the researchers in future. The same issues concern modelling of SWH on non-aggregated data in clusters 2 and 3 (Figures are not provided since they are equivalent to what is shown in Figure 21). Thus for simulation reasons models shown in Table 7 are considered to represent the non-aggregated SWH data well enough.

Cluster_ID	Transf_Type	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	MA(9)	MA(10)	Res. Mean	Res. Std.	Intercept
1	dlog	0.70504	-0.11473	-0.04948	-0.01374	-0.02873	-0.01911	-0.01434	-0.01486	-0.03502	-0.04021	0.0000004	0.110946	0
2	dlog	0.695351	-0.1022	-0.0505	-0.01593	-0.02898	-0.01904	-0.01247	-0.01911	-0.02787	-0.04378	0.0000004	0.112167	0
3	d	0.834734	-0.32859	0.039435	-0.0473	-0.03057	-0.01849	-0.02918	-0.00947	-0.04133	-0.04711	0.000003	0.185239	0

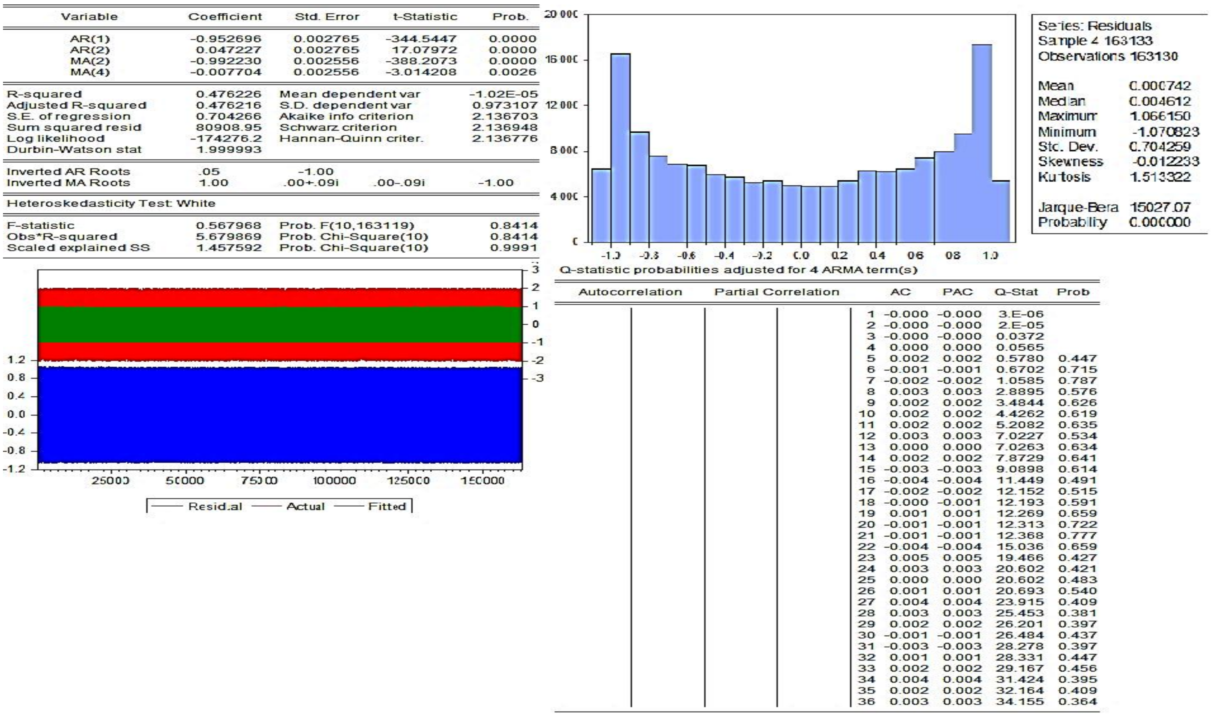
Table 7. *Models of SWH considered for simulation of non-aggregated time series*

These models, however, should not be used for any sorts of precise forecasts of SWH, since the results of such forecasts cannot be reliable.

Data appeared to be much better tangible for non-aggregated time series representing wave directions. Models for both axes of them for each of the clusters are represented below. Note that these models satisfy all of the described above classical assumptions of ARIMA models and can be used not only for simulation but also for forecasts of wave directions. So, ARIMA models used for simulation of wave directions are shown in the Table 8 and described in detail in Figures 22-25.

Axe	Cluster_ID	Transf_Ty	AR(1)	AR(2)	AR(7)	MA(1)	MA(2)	MA(3)	MA(4)	MA(7)	Res. Mear	Res. Std.	Intercept
x	1	d	-0.9527	0.047227	0	0	-0.99223	0	-0.0077		0.000742	0.704259	0
y	1	d	0.053385	0.008722	0	-0.99994	0	0	0	0	-0.00024	0.705316	0
x	2	d	0.071234	0.008721	-0.00541	-0.99926	0	0	0	-0.00073	0.001163	0.705271	0
y	2	d	0.073327	0.009766	0	-0.99997	0	0	0	0	0.000703	0.705101	0

Table 8. *WD models considered for simulation of non-aggregated time series*

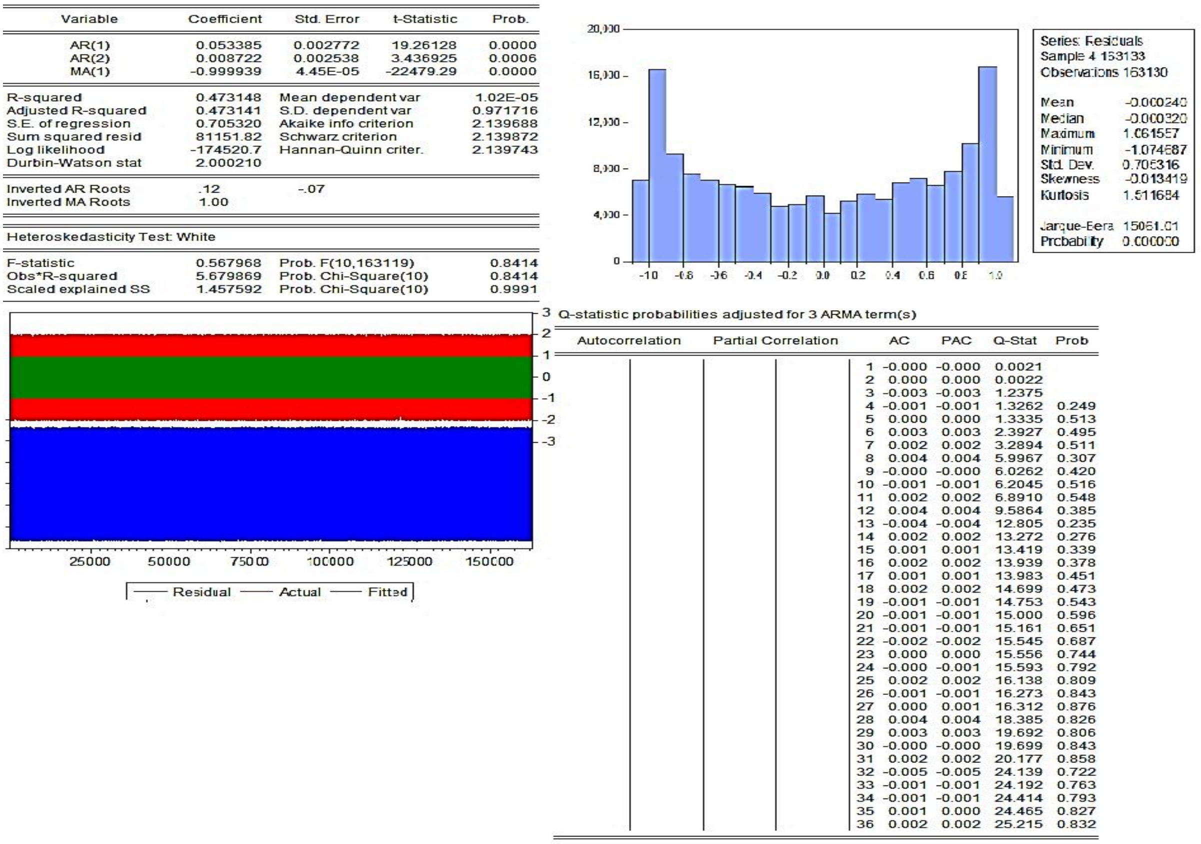


```
Variable          Coefficient   Std. Error   t-Statistic    Prob.

AR(1)             -0.952696     0.002765     -344.5447      0.0000
AR(2)              0.047227     0.002765      17.07972      0.0000
MA(2)             -0.992230     0.002556     -388.2073      0.0000
MA(4)             -0.007704     0.002556     -3.014208      0.0026

R-squared            0.476226   Mean dependent var     -1.02E-05
Adjusted R-squared   0.476216   S.D. dependent var      0.973107
S.E. of regression   0.704266   Akaike info criterion   2.136703
Sum squared resid    80908.95   Schwarz criterion       2.136948
Log likelihood      -174276.2   Hannan-Quinn criter.    2.136776
Durbin-Watson stat   1.999993

Inverted AR Roots     .05          -1.00
Inverted MA Roots    1.00        .00+.09i    .00-.09i     -1.00

Heteroskedasticity Test: White

F-statistic          0.567968   Prob. F(10,163119)        0.8414
Obs*R-squared        5.679869   Prob. Chi-Square(10)      0.8414
Scaled explained SS  1.457592   Prob. Chi-Square(10)      0.9991
```

```
Series: Residuals
Sample 4 163133
Observations 163130

Mean          0.000742
Median        0.004612
Maximum       1.066150
Minimum      -1.070823
Std. Dev.     0.704259
Skewness     -0.012233
Kurtosis      1.513322

Jarque-Bera   15027.07
Probability   0.000000
```

```
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation  Partial Correlation      AC     PAC    Q-Stat   Prob

                                    1 -0.000  -0.000   3.E-06
                                    2 -0.000  -0.000   2.E-05
                                    3 -0.000  -0.000   0.0372
                                    4  0.000   0.000   0.0565
                                    5  0.002   0.002   0.5780   0.447
                                    6 -0.001  -0.001   0.6702   0.715
                                    7 -0.002  -0.002   1.0585   0.787
                                    8  0.003   0.003   2.8895   0.576
                                    9  0.002   0.002   3.4844   0.626
                                   10  0.002   0.002   4.4262   0.619
                                   11  0.002   0.002   5.2082   0.635
                                   12  0.003   0.003   7.0227   0.534
                                   13  0.000   0.000   7.0263   0.634
                                   14  0.002   0.002   7.8729   0.641
                                   15 -0.003  -0.003   9.0898   0.614
                                   16 -0.004  -0.004   11.449   0.491
                                   17 -0.002  -0.002   12.152   0.515
                                   18 -0.000  -0.001   12.193   0.591
                                   19  0.001   0.001   12.269   0.659
                                   20 -0.001  -0.001   12.313   0.722
                                   21 -0.001  -0.001   12.368   0.777
                                   22 -0.004  -0.004   15.036   0.659
                                   23  0.005   0.005   19.466   0.427
                                   24  0.003   0.003   20.602   0.421
                                   25  0.000   0.000   20.602   0.483
                                   26  0.001   0.001   20.693   0.540
                                   27  0.004   0.004   23.915   0.409
                                   28  0.003   0.003   25.453   0.381
                                   29  0.002   0.002   26.201   0.397
                                   30 -0.001  -0.001   26.484   0.437
                                   31 -0.003  -0.003   28.278   0.397
                                   32  0.001   0.001   28.331   0.447
                                   33  0.002   0.002   29.167   0.456
                                   34  0.004   0.004   31.424   0.395
                                   35  0.002   0.002   32.164   0.409
                                   36  0.003   0.003   34.155   0.364
```

Figure 22. *Report on model for cluster 1 of non-aggregated X axe wave directions data*

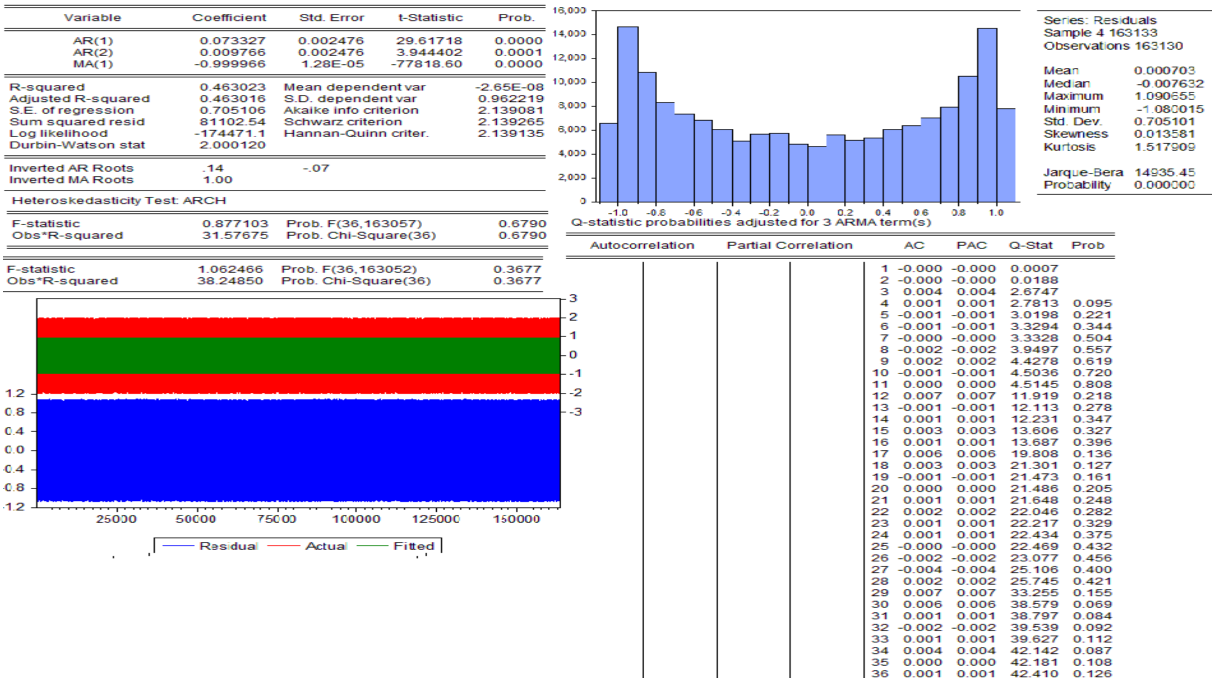


```
Variable            Coefficient   Std. Error   t-Statistic    Prob.

AR(1)                0.053385     0.002772     19.26128     0.0000
AR(2)                0.008722     0.002538     3.436925     0.0006
MA(1)               -0.999939     4.45E-05    -22479.29     0.0000

R-squared            0.473148   Mean dependent var       1.02E-05
Adjusted R-squared   0.473141   S.D. dependent var       0.971716
S.E. of regression   0.705320   Akaike info criterion    2.139688
Sum squared resid    81151.82   Schwarz criterion        2.139872
Log likelihood      -174520.7   Hannan-Quinn criter.     2.139743
Durbin-Watson stat   2.000210

Inverted AR Roots      .12           -.07
Inverted MA Roots     1.00

Heteroskedasticity Test: White

F-statistic          0.567968   Prob. F(10,163119)         0.8414
Obs*R-squared        5.679869   Prob. Chi-Square(10)       0.8414
Scaled explained SS  1.457592   Prob. Chi-Square(10)       0.9991
```

```
Series: Residuals
Sample 4 163133
Observations 163130

Mean          -0.000240
Median        -0.000320
Maximum        1.061557
Minimum       -1.074687
Std. Dev.      0.705316
Skewness      -0.013419
Kurtosis       1.511684

Jarque-Bera    15061.01
Probability    0.000000
```

```
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation   Partial Correlation      AC     PAC    Q-Stat   Prob

                                       1 -0.000 -0.000  0.0021
                                       2  0.000  0.000  0.0022
                                       3 -0.003 -0.003  1.2375
                                       4 -0.001 -0.001  1.3262  0.249
                                       5  0.000  0.000  1.3335  0.513
                                       6  0.003  0.003  2.3927  0.495
                                       7  0.002  0.002  3.2894  0.511
                                       8  0.004  0.004  5.9967  0.307
                                       9 -0.000 -0.000  6.0262  0.420
                                      10 -0.001 -0.001  6.2045  0.516
                                      11  0.002  0.002  6.8910  0.548
                                      12  0.004  0.004  9.5864  0.385
                                      13 -0.004 -0.004  12.805  0.235
                                      14  0.002  0.002  13.272  0.276
                                      15  0.001  0.001  13.419  0.339
                                      16  0.002  0.002  13.939  0.378
                                      17  0.001  0.001  13.983  0.451
                                      18  0.002  0.002  14.699  0.473
                                      19 -0.001 -0.001  14.753  0.543
                                      20 -0.001 -0.001  15.000  0.596
                                      21 -0.001 -0.001  15.161  0.651
                                      22 -0.002 -0.002  15.545  0.687
                                      23  0.000  0.000  15.556  0.744
                                      24 -0.000 -0.001  15.593  0.792
                                      25  0.002  0.002  16.138  0.809
                                      26 -0.001 -0.001  16.273  0.843
                                      27  0.000  0.001  16.312  0.876
                                      28  0.004  0.004  18.385  0.826
                                      29  0.003  0.003  19.692  0.806
                                      30 -0.000 -0.000  19.699  0.843
                                      31  0.002  0.002  20.177  0.858
                                      32 -0.005 -0.005  24.139  0.722
                                      33 -0.001 -0.001  24.192  0.763
                                      34 -0.001 -0.001  24.414  0.793
                                      35  0.001  0.000  24.465  0.827
                                      36  0.002  0.002  25.215  0.832
```

Figure 23. *Report on model for cluster 1 of non-aggregated Y axe wave directions data*

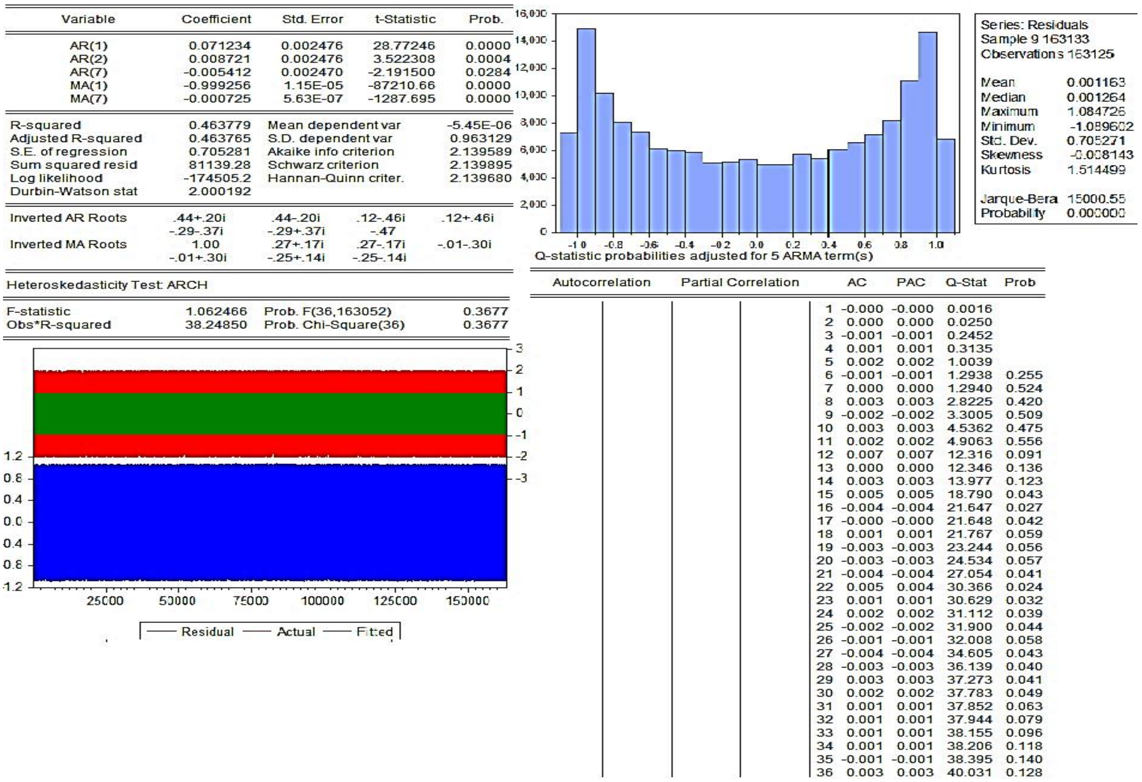


```
Variable            Coefficient   Std. Error   t-Statistic    Prob.

AR(1)                0.073327     0.002476     29.61718     0.0000
AR(2)                0.009766     0.002476     3.944402     0.0001
MA(1)               -0.999966     1.28E-05    -77818.60     0.0000

R-squared            0.463023   Mean dependent var      -2.65E-08
Adjusted R-squared   0.463016   S.D. dependent var       0.962219
S.E. of regression   0.705106   Akaike info criterion    2.139081
Sum squared resid    81102.54   Schwarz criterion        2.139265
Log likelihood      -174471.1   Hannan-Quinn criter.     2.139135
Durbin-Watson stat   2.000120

Inverted AR Roots      .14           -.07
Inverted MA Roots     1.00

Heteroskedasticity Test: ARCH

F-statistic          0.877103   Prob. F(36,163057)         0.6790
Obs*R-squared        31.57675   Prob. Chi-Square(36)       0.6790

F-statistic          1.062466   Prob. F(36,163052)         0.3677
Obs*R-squared        38.24850   Prob. Chi-Square(36)       0.3677
```

```
Series: Residuals
Sample 4 163133
Observations 163130

Mean           0.000703
Median        -0.007632
Maximum        1.090655
Minimum       -1.080015
Std. Dev.      0.705101
Skewness       0.013581
Kurtosis       1.517909

Jarque-Bera    14935.45
Probability    0.000000
```

```
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation   Partial Correlation      AC     PAC    Q-Stat   Prob

                                       1 -0.000 -0.000  0.0007
                                       2 -0.000 -0.000  0.0188
                                       3  0.004  0.004  2.6747
                                       4  0.001  0.001  2.7813  0.095
                                       5 -0.001 -0.001  3.0198  0.221
                                       6 -0.001 -0.001  3.3294  0.344
                                       7 -0.000 -0.000  3.3328  0.504
                                       8 -0.002 -0.002  3.9497  0.557
                                       9  0.002  0.002  4.4278  0.619
                                      10 -0.001 -0.001  4.5036  0.720
                                      11  0.000  0.000  4.5145  0.808
                                      12  0.007  0.007  11.919  0.218
                                      13 -0.001 -0.001  12.113  0.278
                                      14  0.001  0.001  12.231  0.347
                                      15  0.003  0.003  13.606  0.327
                                      16  0.001  0.001  13.687  0.396
                                      17  0.006  0.006  19.808  0.136
                                      18  0.003  0.003  21.301  0.127
                                      19 -0.001 -0.001  21.473  0.161
                                      20  0.000  0.000  21.486  0.205
                                      21  0.001  0.001  21.648  0.248
                                      22  0.002  0.002  22.046  0.282
                                      23  0.001  0.001  22.217  0.329
                                      24  0.001  0.001  22.434  0.375
                                      25 -0.000 -0.000  22.469  0.432
                                      26 -0.002 -0.002  23.077  0.456
                                      27 -0.004 -0.004  25.106  0.400
                                      28  0.002  0.002  25.745  0.421
                                      29  0.007  0.007  33.255  0.155
                                      30  0.006  0.006  38.579  0.069
                                      31  0.001  0.001  38.797  0.084
                                      32 -0.002 -0.002  39.539  0.092
                                      33  0.001  0.001  39.627  0.112
                                      34  0.004  0.004  42.142  0.087
                                      35  0.000  0.000  42.181  0.108
                                      36  0.001  0.001  42.410  0.126
```

Figure 24. *Report on model for cluster 2 of non-aggregated X axe wave directions data*



```
Variable        Coefficient   Std. Error   t-Statistic   Prob.

AR(1)            0.071234     0.002476     28.77246     0.0000
AR(2)            0.008721     0.002476     3.522308     0.0004
AR(7)           -0.005412     0.002470    -2.191500     0.0284
MA(1)           -0.999256     1.15E-05    -87210.66     0.0000
MA(7)           -0.000725     5.63E-07    -1287.695     0.0000

R-squared              0.463779   Mean dependent var     -5.45E-06
Adjusted R-squared     0.463765   S.D. dependent var      0.963129
S.E. of regression     0.705281   Akaike info criterion   2.139589
Sum squared resid      81139.28   Schwarz criterion       2.139895
Log likelihood        -174505.2   Hannan-Quinn criter.    2.139680
Durbin-Watson stat     2.000192

Inverted AR Roots     .44+.20i     .44-.20i     .12-.46i     .12+.46i
                     -.29-.37i    -.29+.37i       -.47
Inverted MA Roots       1.00       .27+.17i     .27-.17i    -.01-.30i
                     -.01+.30i    -.25+.14i    -.25-.14i

Heteroskedasticity Test: ARCH

F-statistic        1.062466   Prob. F(36,163052)        0.3677
Obs*R-squared      38.24850   Prob. Chi-Square(36)      0.3677
```

```
Series: Residuals
Sample 9 163133
Observations 163125

Mean          0.001163
Median        0.001264
Maximum       1.084726
Minimum      -1.089602
Std. Dev.     0.705271
Skewness     -0.008143
Kurtosis      1.514499

Jarque-Bera   15000.55
Probability   0.000000
```

```
Q-statistic probabilities adjusted for 5 ARMA term(s)

Autocorrelation   Partial Correlation        AC      PAC    Q-Stat   Prob

                                         1 -0.000  -0.000   0.0016
                                         2  0.000   0.000   0.0250
                                         3 -0.001  -0.001   0.2452
                                         4  0.001   0.001   0.3135
                                         5  0.002   0.002   1.0039
                                         6 -0.001  -0.001   1.2938  0.255
                                         7  0.000   0.000   1.2940  0.524
                                         8  0.003   0.003   2.8225  0.420
                                         9 -0.002  -0.002   3.3005  0.509
                                        10  0.003   0.003   4.5362  0.475
                                        11  0.002   0.002   4.9063  0.556
                                        12  0.007   0.007   12.316  0.091
                                        13  0.000   0.000   12.346  0.136
                                        14  0.003   0.003   13.977  0.123
                                        15  0.005   0.005   18.790  0.043
                                        16 -0.004  -0.004   21.647  0.027
                                        17 -0.000  -0.000   21.648  0.042
                                        18  0.001   0.001   21.767  0.059
                                        19 -0.003  -0.003   23.244  0.056
                                        20 -0.003  -0.003   24.534  0.057
                                        21 -0.004  -0.004   27.054  0.041
                                        22  0.005   0.004   30.366  0.024
                                        23  0.001   0.001   30.629  0.032
                                        24  0.002   0.002   31.112  0.039
                                        25 -0.002  -0.002   31.900  0.044
                                        26 -0.001  -0.001   32.008  0.058
                                        27 -0.004  -0.004   34.605  0.043
                                        28 -0.003  -0.003   36.139  0.040
                                        29  0.003   0.003   37.273  0.041
                                        30  0.002   0.002   37.783  0.049
                                        31  0.001   0.001   37.852  0.063
                                        32  0.001   0.001   37.944  0.079
                                        33  0.001   0.001   38.155  0.096
                                        34  0.001   0.001   38.206  0.118
                                        35 -0.001  -0.001   38.395  0.140
                                        36  0.003   0.003   40.031  0.128
```

Figure 25. *Report on model for cluster 2 of non-aggregated Y axe wave directions data*

5. *Description of the simulation tool*

Discrete event simulation tool for evaluation of supply vessel schedules' robustness and their a posteriori improvements is described in this chapter. The chapter consists of sections dedicated to description of input and output files, routing and weather modelling algorithms, interface, robustness parameters and the way they get estimated and finally multicriteria ranking algorithms.

5.1 *Input and output files*

In this section input and output files for the simulation tool are addressed.

5.1.1 *Input files description*

Input parameters

Firstly, let us address input data and its formats. Several important files are used for setting parameters of simulation. These files are: Vessels.csv, input.csv, installations_data.csv, WeatherData\\WeatherData.dat, WeatherData\\common.dat, WeatherData\\models.dat, WeatherData\\modelled_weather.dat. Their detailed description is presented below.

Vessels.csv, which contains such parameters of vessels as designed speed, maximal and minimal speeds (in knots), deadweight (in tons), all sorts of fuel consumptions and the corresponding to them costs.

#											
2											
#Vessel	Id	Dead Wei	Capacity	Speed	MinSpeed	MaxSpee	FCCosts(k	FCSailing(	FCBase(to	FCInstalla	Start
TBN1	0	4847	1000	12	6	20	5000	0.43	0.08	0.26	16
TBN3	1	4847	1000	12	6	20	5000	0.43	0.08	0.26	16
TBN3	2	4847	1000	12	6	20	5000	0.43	0.08	0.26	16

Table 9. *Input file format for Vessels.csv*

Input.csv, which contains information about schedules of vessels including such parameters as expected arrival, discharge and departure times, and vessels that participate in the given leg. Below one can find an example of this file:

#	N				
1	19	19			
Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	1.137107	1.333327	1.666667	TBN1	0
OFP	1.137107	1.333327	1.666667	TBN1	0
WEP	2.10108	2.10107	2.23858	TBN1	0
SLE	2.23927	2.29167	2.49583	TBN1	0
DRA	2.56755	2.56755	2.6613	TBN1	0
OFP	3.13711	3.33333	3.66667	TBN1	0
FBS	3.13711	3.33333	3.66667	TBN1	0
OFP	3.13711	3.33333	3.66667	TBN1	0
WEP	4.10108	4.10107	4.23858	TBN1	0
SLE	4.23928	4.29167	4.49583	TBN1	0
VOL	4.51325	4.51325	4.65909	TBN1	0
OFP	5.17427	5.33333	5.66667	TBN1	0
FBS	5.17427	5.33333	5.66667	TBN1	0
OFP	5.17427	5.33333	5.66667	TBN1	0
WEP	6.10108	6.10108	6.23858	TBN1	0
SLE	6.23928	6.29167	6.49583	TBN1	0
GLI	6.57026	6.57026	6.73693	TBN1	0
OFP	7.26368	7.33333	8.66667	TBN1	0
FBS	7.26368	7.33333	8.66667	TBN1	0

Table 10. *Input file format for Input.csv*

Installations_data.csv, which contains geographical coordinates of the installations, their IDs and service durations in conditions of perfect weather, their working hours and cranes available.

#	Size						
12	7						
Node	Id	LatDeg	LonDeg	LayTime	Open	Close	Cranes
FBS	0	59	5.66025	8	8	16	3
DRA	1	58.18833	2.475	2.25	7	19	1
GDR	2	58.83147	1.724972	2.9	0	24	1
GLI	3	58.7	1.666667	4	7	19	1
GRA	4	59.16433	2.485167	3	0	24	1
HDA	5	59.57333	2.228333	4.5	7	19	1
OFP	6	59.05108	5.244122	0	0	24	0
OVA	7	58.569	1.702861	2.9	0	24	1
SLE	8	58.36667	1.911667	4.9	7	19	1
TRL	9	58.63014	1.737639	2.9	0	24	1
VOL	10	58.45	1.9	3.5	0	24	1
WEP	11	58.36944	1.911111	3.3	0	24	1

Table 11. *Input file format for Installations_data.csv*

sim_params.csv, which contains parameters of weather simulation for the whole time horizon to be addressed. In this file cell (2,1) sets ID of the number of 3-hour observation, at which the simulation begins (e.g. simulation begins at 12th hour of the year, then value for (2,1) should be 4), cell (2,1) sets the corresponding value for the end of the simulation, cell (2,3) sets the number of ARIMA-based weather parameters to be considered, cell (2,4) sets numbers of clusters for these parameters delimited with ";" sign, cell (2,5) sets historical horizon of the data to be considered, which should be greater or equal to the maximal order of AR or MA components of weather parameters. Cell (2,6) contains total number of replications to be carried out (note that this is an approximate number and it can be adjusted so that each sub period has the same amount of replications to be run, in case the number input already satisfies this conditions, it is exact). Cell (2, 7) contains the value to describe cluster crossing algorithm (see in the corresponding chapter below) and finally cell (2, 8) contains Δt for such an algorithm, cell (2, 9) contains an id of an a posteriori improvement type.

#Start_Hour	Finish_Hour	Weather_Parameters_Count	Clusters	Horizon	Replicatio	ClusterCrossing	Dt	Impov.
2209	6576	3	3;2;2	15	100	1	0.1	0

Table 12. *Input file format for sim_params.csv*

weatherData\\common.dat, which contains parameters of weather simulation for a current replication. In this file cell (2,1) sets ID of the number of 3-hour observation, at which the simulation begins (e.g. simulation begins at 12th hour of the year, then value for (2,1) should be 4), cell (2,1) sets the corresponding value for the end of the simulation, cell (2,3) sets the number of ARIMA-based weather parameters to be considered, cell (2,4) sets numbers of clusters for these parameters delimited with ";" sign, cell (2,5) sets historical horizon of the data to be considered, which should be greater or equal to the maximal order of AR or MA components of weather parameters.

Start_Hour	Finish_Hour	Weather_Parameters_Count	Clusters	Horizon
2192	2331	3	3;2;2	15

Table 13. *Input file format for common.dat*

weatherData\\models.dat contains weather ARIMA models. This file is less intuitively clear, thence a more detailed description of it will be provided. So, weather parameters themselves are set in rows *i* starting from row 2, in particular, cell (i,1) sets ID of the corresponding to *i*-th row weather parameter, cell (i,2) sets the cluster, where this parameter is relevant, cell(i,3) sets the ID for the beginning of time interval, during which the corresponding parameter is relevant, cell(i,4) sets the end of the corresponding period, cell (i,5) sets type of data transformation, so that “2” corresponds to the first difference of the natural logarithm of real data, “0” corresponds to the first difference of real data and “1” corresponds to the second difference of real data, cell (i, 6) sets coefficients of AR components delimited with “;” sign, whilst their number sets the order of auto regression, cell (i,7) sets coefficients of MA component of the model identically to the way AR components are set, cell(i,8) sets mathematical expectation and standard deviation of the residuals of the corresponding model delimited with “;” sign, and finally cell (i,9) sets value of the intercept of the corresponding model.

#Weather	Cluster_I	Rel_Start_	Rel_Fin_H	Transf_Ty	AR	MA	RES	Intercept
0	0	0	471	2	0.737338;	0.546952;-	0.000306;	0
0	0	472	982	2	0.348709;	0.842745;-	-0.00018;	-0.00114
0	0	983	1998	2	0.765681;	0.071897;	0.0000048	0
0	0	1999	2927	2	0.737338;	0.546952;-	0.000306;	0
0	1	983	1998	2	0.244788;	0.824285;	0.0000070	0
0	1	1999	2927	2	1.159743;-	0;0;0;0;0;	0.000695;	0
0	1	0	477	2	1.159743;-	0;0;0;0;0;	0.000695;	0
0	1	478	982	2	0.705389;	0.352350;-	-0.000184;	-0.00114
0	2	983	1998	2	0.449812;	0.268838;	0.000184;	0
0	2	1999	2495	2	1.943454;-	-0.979026;	0.000795;	0
0	2	2496	2927	2	0.863824;	0;-0.67052	-0.000163;	0
0	2	0	471	2	0.863824;	0;-0.67052	-0.000163;	0
0	2	472	982	2	0.422062;	0.394490;	-0.000578;	0
1	0	0	2927	0	0.069804	-0.9986	-0.000302;	0
1	1	0	2927	0	0.04916	-0.99539	-0.0000064	0
2	0	0	2927	0	0	-0.99851	-0.000252;	0
2	1	0	2927	0	0.076195	-0.9984	0.000432;	0

Table 14. *Input file format for models.dat*

weatherData\\WeatherData.dat, which contains input data of the statistical observations of weather parameters preceding the simulation in order to have basis of both autoregressive and moving average data so as to begin the simulation.

Hour	WheightC	WH_RES_	WheightC	WH_RES_	WheightC	WH_RES_	x_1	WDX_RES_	x_2	WDX_RES_	y_1	WDY_RES_	y_2	WDY_RES_2
0	3.227041	0	3.330134	0	2.419643	0	-0.10491	0	0.008881	0	0.061193	0	0.033882	0
3	3.321173	0	3.429464	0	2.489286	0	0.111613	0	-0.02115	0	-0.08741	0	0.027127	0
6	3.447194	0	3.490179	0	2.601786	0	-0.08107	0	0.061545	0	0.25084	0	-0.05096	0
9	3.492857	0	3.495759	0	2.621429	0	-0.01208	0	0.064934	0	-0.00948	0	-0.00063	0
12	3.444643	0	3.451786	0	2.633929	0	-0.01452	0	-0.01051	0	-0.03044	0	0.036716	0
15	3.365306	0	3.392634	0	2.591071	0	0.041869	0	0.053415	0	-0.02441	0	-0.0356	0
18	3.351786	0	3.385938	0	2.528571	0	-0.02695	0	-0.00701	0	0.111961	0	0.01404	0
21	3.295918	0	3.367857	0	2.458929	0	-0.13282	0	0.011631	0	0.043378	0	0.009097	0

Table 15. *Input file format for WeatherData.dat*

weatherData\\Modeled_Weather.dat, which contains simulated weather for a current replication basing on the given set of models based in turn on a given set of input data with respect to the algorithm, presented in the especially dedicated to it section below.

No	W_H:CL-0	W_H:CL-0	W_H:CL-1	W_H:CL-1	W_H:CL-2	W_H:CL-2	W_DX:CL-	W_DX:CL-	W_DX:CL-	W_DX:CL-	W_DY:CL-	W_DY:CL-	W_DY:CL-	W_DY:CL-1:Res
17	2.381677	-0.28986	2.418556	-0.28986	1.644377	-0.28986	-1.10621	-1.12114	-1.10659	-1.12066	-1.12289	-1.12092	-1.07606	-1.120657664
18	2.427718	0.272538	2.464585	0.272538	1.69261	0.272538	0.970328	1.054117	0.97375	1.053659	0.945697	1.053907	0.999184	1.053659322
19	2.554152	-0.00256	2.591256	-0.00256	1.82076	-0.00256	0.034442	-0.00989	0.049662	-0.00989	0.020545	-0.00989	0.09487	-0.009890498
20	2.775905	0.143833	2.813363	0.143833	2.043566	0.143833	0.551988	0.556309	0.610103	0.556067	0.52697	0.556198	0.518766	0.556067397
21	3.062223	0.145869	3.100029	0.145869	2.330281	0.145869	0.588231	0.564184	0.66754	0.563939	0.57655	0.564072	0.596874	0.563939317
22	2.997212	-0.23678	3.035282	-0.23678	2.265157	-0.23678	-0.88584	-0.91584	-0.87467	-0.91545	-0.90352	-0.91566	-0.84282	-0.91544535
23	2.984642	0.1314	3.022865	0.1314	2.252171	0.1314	0.439608	0.508219	0.439641	0.507998	0.425508	0.508118	0.432863	0.507998407
24	3.032977	0.022346	3.071248	0.022346	2.299989	0.022346	0.096691	0.08642	0.126003	0.086383	0.083018	0.086403	0.109327	0.086382593
25	3.298394	0.238031	3.336639	0.238031	2.56494	0.238031	0.916926	0.920649	0.910973	0.92025	0.893347	0.920466	0.955086	0.920249629

Table 16. *Input file format for Modeled_Weather.dat*

These data files are imported into the model (into corresponding variables or expressions) before each run of the simulation by means of VBA code. Vessels.csv, input.csv, installations_data.csv, WeatherData\\WeatherData.dat, WeatherData\\common.dat are imported at the beginning of the simulation, whereas WeatherData\\modelled_weather.dat is generated and then imported before the beginning of each replication. A sample of code for importing vessels.csv is presented in listing A-2 below.

5.1.2 Output files description

Output parameters

Firstly, let us address the output data and its format. Several important files are used for analyzing results of the simulation. These files are: keyfactors.csv and output.csv. Their detailed description is presented below.

Output.csv, which contains such parameters of simulated schedules as simulated arrival, discharge and departure times, scheduled arrival, discharge and departure times, counter of visits to the installation during the given time horizon, geographical coordinates of the arrival point (so that one can check the navigation is correct), length of the route from the origin to the current destination, corresponding to it travelling time, servicing time at the current destination, waiting for service time, sailing and servicing fuel consumptions, total fuel consumptions and finally total fuel costs of the current leg. An example of this file is shown in Table 17.

Keyfactors.csv, which contains such parameters as estimates of mathematical expectation of service level, tardiness and deviations from the scheduled arrival, discharge and departure times as well as all sorts of fuel consumptions and fuel costs; corresponding standard deviations, margins of errors and bounds of the confidence intervals of these parameters. An example of this file is shown in Table 18.

Locati	VesID	ArrTin	ExpAr	Distch	ExpDi	DepTi	ExpDe	VisitI	Lattitu	Longli	Distan	Sailing	WaitF	WaitF	Servic	ExpSe	FCSail	FCBas	FCInst	FCTot	FCTot
FBS	TBN1	64	64	64	64	64	64	1	59	5.66	0	0	0	0	0	0	0	0	0	0	0
FBS	TBN3	40	40	40	40	40	40	2	59	5.66	0	0	0	0	0	0	0	0	0	0	0
OFP	TBN3	41.56	41.56	41.56	41.56	41.56	41.56	1	59.05	5.244	24.48	1.562	0	0	0	0	0.389	0	0	0.389	1944
GRA	TBN3	52.38	49.85	52.38	49.85	55.38	52.85	1	59.16	2.485	158	10.82	0	0	3	3	2.274	0	0.78	3.054	15269
GDR	TBN3	58.09	55.94	58.09	55.94	60.99	58.84	1	58.83	1.725	57.14	2.707	0	0	2.9	2.9	1.579	0	0.754	2.333	11666
GLI	TBN3	61.68	59.65	61.68	59.65	65.68	63.65	1	58.7	1.667	15	0.687	0	0	4	4	0.401	0	1.04	1.441	7205
OFP	TBN1	65.46	65.46	65.46	65.46	65.46	65.46	2	59.05	5.244	24.48	1.457	0	0	0	0	0.363	0	0	0.363	1813
VOL	TBN1	78.18	76.34	78.18	76.34	81.68	79.84	1	58.45	1.9	204.1	12.73	0	0	3.5	3.5	2.935	0	0.91	3.845	19225
TRL	TBN3	66.14	64.12	66.14	64.12	69.04	67.02	1	58.63	1.738	8.786	0.459	0	0	2.9	2.9	0.164	0	0.754	0.918	4590
OVA	TBN3	69.41	67.41	69.41	67.41	72.31	70.31	1	58.57	1.703	7.091	0.373	0	0	2.9	2.9	0.134	0	0.754	0.888	4440
WEP	TBN3	73.65	71.67	73.65	71.67	76.95	74.97	1	58.37	1.911	25.28	1.343	0	0	3.3	3.3	0.447	0	0.858	1.305	6524
OFP	TBN3	88.85	88.85	88.85	88.85	88.85	88.85	3	59.05	5.244	206.8	11.9	0	0	0	0	2.961	0	0	2.961	14803
SLE	TBN1	82.18	80.35	82.18	80.35	87.08	85.25	1	58.37	1.912	9.291	0.496	0	0	4.9	4.9	0.148	0	1.274	1.422	7108
OVA	TBN1	88.47	86.63	88.47	86.63	91.37	89.53	2	58.57	1.703	25.57	1.392	0	0	2.9	2.9	0.397	0	0.754	1.151	5753
FBS	TBN3	90.41	87.46	104	104	112	112	3	59	5.66	24.48	1.559	0	13.59	8	8	0.388	1.727	0	2.115	10576
TRL	TBN1	91.75	89.91	91.75	89.91	94.65	92.81	2	58.63	1.738	7.091	0.381	0	0	2.9	2.9	0.11	0	0.754	0.864	4320
GDR	TBN1	95.86	94.02	95.86	94.02	98.76	96.92	2	58.83	1.725	22.4	1.208	0	0	2.9	2.9	0.388	0	0.754	1.142	5710
GRA	TBN1	101.8	100	101.8	100	104.8	103	2	59.16	2.485	57.14	2.995	0	0	3	3	1.168	0	0.78	1.948	9740
HDA	TBN1	107	105.6	107	105.6	112.2	110.1	1	59.57	2.228	47.75	2.246	0	0	5.2	4.5	1.316	0	1.352	2.668	13340
OFP	TBN3	113.7	113.7	113.7	113.7	113.7	113.7	4	59.05	5.244	24.48	1.722	0	0	0	0	0.429	0	0	0.429	2143
OFP	TBN1	126.9	126.9	126.9	126.9	126.9	126.9	5	59.05	5.244	180.7	14.73	0	0	0	0	3.665	0	0	3.665	18323
GRA	TBN3	126.8	121.9	126.8	121.9	129.9	124.9	3	59.16	2.485	158	13.03	0	0	3.15	3	3.704	0	0.819	4.523	22614
FBS	TBN1	128.7	121.2	128.7	128	136.7	136	4	59	5.66	24.48	1.751	0	0	8	8	0.436	0.64	0	1.076	5379
WEP	TBN3	132.9	129.9	132.9	129.9	136.2	133.2	2	58.37	1.911	94.38	2.953	0	0	3.3	3.3	5.878	0	0.858	6.736	33679
SLE	TBN3	136.2	133.3	146.2	133.3	151.1	138.2	2	58.37	1.912	0.311	#####	0	10	4.9	4.9	#####	0	3.874	3.881	19407
OFP	TBN1	138.7	138.7	138.7	138.7	138.7	138.7	6	59.05	5.244	24.48	2.026	0	0	0	0	0.504	0	0	0.504	2520
GRA	TBN1	148.8	145.9	148.8	145.9	152.2	148.9	4	59.16	2.485	158	10.1	0	0	3.362	3	4.15	0	0.874	5.024	25120
OFP	TBN3	164.1	164.1	164.1	164.1	164.1	164.1	7	59.05	5.244	206.9	13.07	0	0	0	0	3.253	0	0	3.253	16263
HDA	TBN1	153.6	151.4	153.6	151.4	158.1	155.9	2	59.57	2.228	47.75	1.452	0	0	4.5	4.5	2.89	0	1.17	4.06	20298
GDR	TBN1	160.9	160.6	160.9	160.6	163.8	163.5	3	58.83	1.725	87.33	2.732	0	0	2.9	2.9	5.438	0	0.754	6.192	30960
TRL	TBN1	164.7	164.8	164.7	164.8	167.6	167.7	3	58.63	1.738	22.4	0.994	0	0	2.9	2.9	0.629	0	0.754	1.383	6916
FBS	TBN3	165.6	150.7	176	152	184	160	5	59	5.66	24.48	1.507	0	10.35	8	8	0.375	1.468	0	1.843	9216
OVA	TBN1	168	168	168	168	170.9	170.9	3	58.57	1.703	7.091	0.371	0	0	2.9	2.9	0.137	0	0.754	0.891	4453
WEP	TBN1	172.3	172.3	172.3	172.3	175.6	175.6	3	58.37	1.911	25.28	1.361	0	0	3.3	3.3	0.466	0	0.858	1.324	6618
DRA	TBN1	177.6	177.7	177.6	177.7	179.9	179.9	1	58.19	2.475	38.63	2.06	0	0	2.22	2.25	0.695	0	0.577	1.272	6359
OFP	TBN1	191	191	191	191	191	191	9	59.05	5.244	186.8	11.16	0	0	0	0	2.778	0	0	2.778	13891
OFP	TBN3	185.6	185.6	185.6	185.6	185.6	185.6	8	59.05	5.244	24.48	1.578	0	0	0	0	0.393	0	0	0.393	1963
GRA	TBN3	195.7	169.9	195.7	169.9	198.7	172.9	5	59.16	2.485	158	10.17	0	0	3	3	2.36	0	0.78	3.14	15701
FBS	TBN1	192.5	191.3	200	200	208	232	6	59	5.66	24.48	1.497	0	7.479	8	8	0.373	1.238	0	1.611	8055

Table 17. *Output file format for output.csv*

E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.929931973	0.003843848	0.00011345	0.929818523	0.930045422
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.657036904	0.020717575	0.001772211	0.655264693	0.658809114
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.476190476	0.048739649	0.009322745	0.466867731	0.485513222
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.573333333	0.021585808	0.00184648	0.571486853	0.575179814
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
19.24414817	3.210392816	0.614072426	18.63007575	19.8582206
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
19.43884376	3.20501906	0.613044554	18.8257992	20.05188831
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
13.7209137	7.670223938	6.723247714	6.997665988	20.44416142
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
13.76111367	7.6926964	6.742945696	7.018167969	20.50405936
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
8.833435094	5.3500307	1.853691064	6.97974403	10.68712616
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
8.939160827	5.372896015	1.861613491	7.077547336	10.80077432
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
8.658272583	5.059305795	1.752960024	6.905312559	10.41123261
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
8.758225554	5.078397715	1.759575036	6.998650518	10.51780059
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
9.429059456	4.973515787	1.723235302	7.705824154	11.15229476
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
10.07751859	5.670273092	1.964649392	8.112869201	12.04216798
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1061.376906	99.27593615	18.98914509	1042.38776	1080.366051
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
71.98451308	6.605427173	1.263462425	70.72105065	73.2479755
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
613.7256736	57.43286152	10.98555181	602.7401218	624.7112254
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1747.087092	163.2790471	31.23143066	1715.855662	1778.318523
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
8735435.461	816395.2354	156157.1533	8579278.308	8891592.614

Table 18. *Output file format for keyfactors.csv*

5.2 ARIMA based weather simulation

Weather simulation is carried out basing on ARIMA models. The following algorithm is used to model all weather parameters simultaneously.

ARIMA based weather modelling algorithm:

- **Store** historical data of the observations for the models and the corresponding residuals into the relevant data structure (Array, List, Array-List etc.) after making a relevant data transformation ((4.4.1),(4.4.2),(4.7.1)-(4.7.4),(4.7.5)-(4.7.7)).
- **For each** 3-hour based time interval number *i* of the simulation:
    - ✓ **Generate** a random variable $r \sim N(0,1)$ by means of any of the relevant methods (CLT-based approach, described below is based in the presented simulation tool).
    - ✓ **Simulate** ARIMA for each active at current time interval *i* ARIMA model from the set of models for a given set of weather parameters using the same $r \sim N(0,1)$ and **store** the generated data.
    - ✓ **Run** ARIMA forecast for both each active and inactive at current time interval *i* ARIMA model from the set of models for a given set of weather parameters and **store** the generated data.
    - ✓ **Make** the inverse data transformation and **store** modelled weather into the output file.

Random variable $r \sim N(0,1)$ generation algorithm

- **Set** the sample length N, S =0, m=0.5, sd=$\frac{1}{\sqrt{12N}}$
- **For each** $i = \overline{1,N}$:
    - ✓ **Generate** a uniformly distributed random number $u \sim U(0,1)$**.**
    - ✓ **Add** *u* to *S:* $S = S + u$.
- **Divide** *S* by *N:* $S = \frac{S}{N}$
- **Standardize** *S*:

$$r = \frac{S - m}{sd}, \; r \sim N(0,1) . \qquad (5.2.1)$$

Simulate ARIMA(P,0,Q) algorithm

- **For** all relevant *t*:
  - ✓ **Calculate** the residual for time *t*:

$$\varepsilon_{p,c,t} = \sigma_{p,c} r_t + \mu_{p,c}, p \in \mathrm{P}, c \in \mathrm{Z}, \tag{5.2.2}$$

where P and Z are sets of weather parameters and clusters correspondingly.

  - ✓ **Calculate** the simulated value for weather at time *t* corresponding to the current time interval *i*:

$$w_{p,c,t} = i_{p,c,t} + \sum_{\tau=t-P}^{t-1} \alpha_{P-\tau} w_{p,c,\tau} + \sum_{\tau=t-Q}^{t-1} \beta_{Q-\tau} \varepsilon_{p,c,\tau} + \varepsilon_{p,c,t}, p \in \mathrm{P}, c \in \mathrm{Z}, \tag{5.2.3}$$

where P and Z are sets of weather parameters and clusters correspondingly.

Forecast ARIMA (P,0,Q) algorithm

- **For** all relevant *t*:
  - ✓ **Calculate** the forecasted value for weather at time *t* corresponding to the current time interval *i*:

$$\hat{w}_{p,c,t} = i_{p,c,t} + \sum_{\tau=t-P}^{t-1} \alpha_{P-\tau} w_{p,c,\tau} + \sum_{\tau=t-Q}^{t-1} \beta_{Q-\tau} \varepsilon_{p,c,\tau}, p \in \mathrm{P}, c \in \mathrm{Z}, \tag{5.2.4}$$

where P and Z are sets of weather parameters and clusters correspondingly.

Inverse data transformation algorithm

- **If** the straight transformation was those shown in (4.7.3) or (4.7.6) then the inverse transformation is (notation is left as it is in the 7th chapter):

$$\tilde{w}_{c,m,d,h+3,t} = \bar{d}_{c,m,d,h,t} + \tilde{w}_{c,m,d,h,t}. \tag{5.2.5}$$

- **If**, however, the straight transformation is (4.7.4) or (4.7.7) then the inverse transformation is:

$$\tilde{w}_{c,m,d,h+3,t} = \tilde{w}_{c,m,d,h,t} e^{\bar{v}_{c,m,d,h,t}}. \tag{5.2.6}$$

These algorithms are incorporated into C# code and run via weather_modelling.exe. The source code for ARIMA based weather modelling is presented in listing A-3 in the Appendix.

An example of such ARIMA based output for 10 different simulations and the original time series of significant wave heights as well as wave directions for x axe for the beginning of year 2013 is presented in Figures 26, 27 and 28 below.

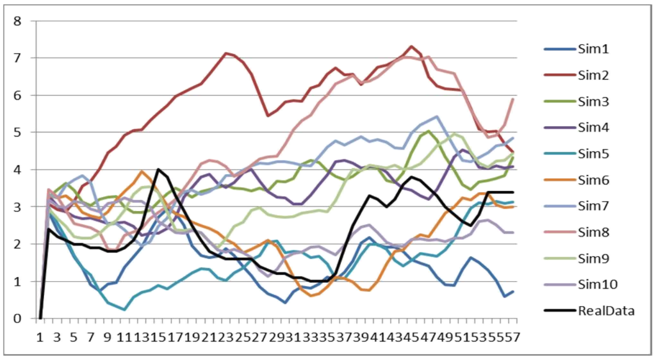


Figure 26. *A sample of ARIMA based simulated time series of SWH at cluster 1*

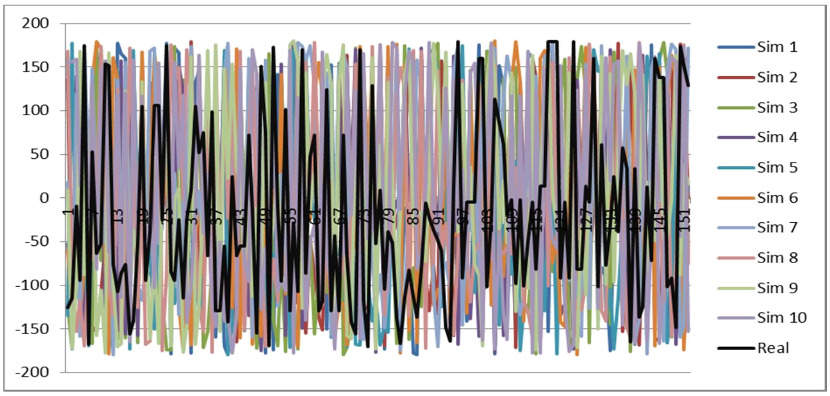


Figure 27. *A sample of ARIMA based simulated time series of WD at cluster 1*

Time series for significant wave heights or/and wave directions are highly correlated between the clusters, thus, this approach is incorporated in the ARIMA-based simulation model, practical implementation and results of overcoming such an issue are shown in Figure 28.

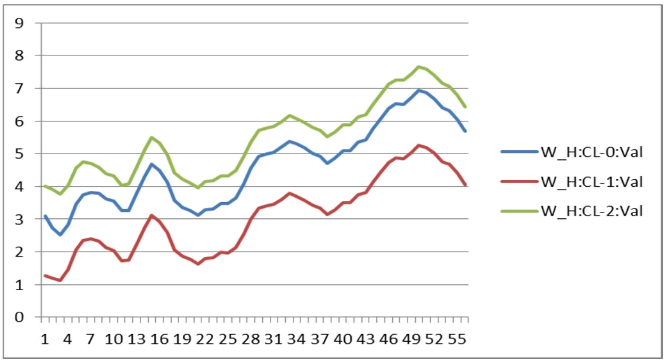


Figure 28. *Three ARIMA based simulated time series of SWH in 3 different clusters*

5.3 Introduction into the maritime navigation

Geographic coordinate system – is a coordinate system that enables every location on the Earth to be specified by a set of numbers or letters. The coordinates are often chosen in such a way that one of the numbers represents vertical position, and two or three of the numbers represent horizontal position. A common choice of coordinates is latitude, longitude and elevation (Pros-Wellenhof and Bernhard 2007).

Latitude – is the angle between the equatorial plane and the straight line that passes through that point and is normal to the surface of a reference ellipsoid which approximates the shape of the Earth (is defined in range $[-90^\circ, 90^\circ]$).

Longitude – is the angle east or west from a reference meridian to another meridian that passes through that point. All meridians are halves of great ellipses (often improperly called great circles), which converge at the north and south poles (is defined in range $[-180^\circ, 180^\circ]$).

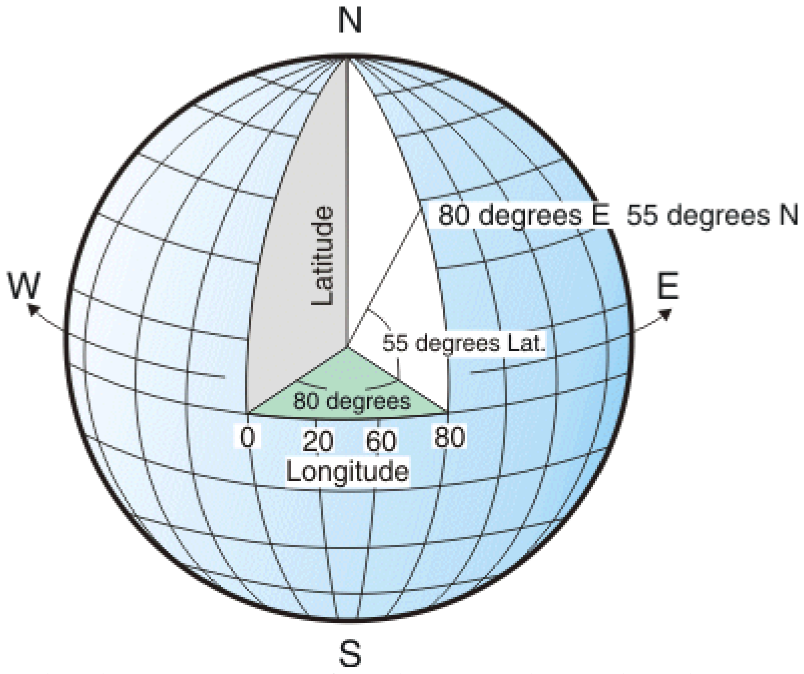


Figure 29. *A graphical representation of a sphere coordinates based system of geographical coordinates*

Spherical distance (or the great-circle/orthodromic distance) – is the shortest distance between two points on the surface of a sphere, measured along the surface of the sphere (as opposed to a straight line through the sphere's interior). Spherical distance between points (φ_1, λ_1) and (φ_2, λ_2) might be calculated by means of the Haversine formula, which is represented in (5.3.1).

$$\begin{aligned}&\Delta\varphi = \varphi_2 - \varphi_1, \Delta\lambda = \lambda_2 - \lambda_1\\&a = \sin^2(\Delta\varphi/2) + \cos(\varphi_2)\cos(\varphi_1)\sin^2(\Delta\lambda/2)\\&c = 2\mathrm{atan2}(\sqrt{a}, \sqrt{(1\text{-}a)})\\&d = R \times c\end{aligned}, \tag{5.3.1}$$

where *c* is the Earth radius equal to 6371 Km.

Haversine formula is incorporated by means of the VBA function, shown in listing A-4 in the appendix.

Bearing – is the angle between a line connecting us (φ_1, λ_1) and another object (φ_2, λ_2), and a north-south line. Bearing is calculated by means of the following formula:

$$\theta = \mathrm{atan2}(\ \sin(\Delta\lambda).\cos(\varphi_2),\ \cos(\varphi_1)\sin(\varphi_2)\ \text{-}\ \sin(\varphi_1)\cos(\varphi_2)\cos(\Delta\lambda)\ ). \tag{5.3.2}$$

This formula is incorporated into Arena by means of VBA function, shown in listing A-5.

Calculation of the destination point's latitude and longitude (φ_2, λ_2) with the initial coordinates (φ_1, λ_1), bearing (φ_1, λ_1) and travelling distance d given is carried out by means of the corresponding formulas:

$$\varphi_2 = \mathrm{asin}(\ \sin(\varphi_1)\cos(d/R) + \cos(\varphi_1)\sin(d/R)\cos(\theta)\ ), \tag{5.3.3}$$

$$\lambda_2 = \lambda_1 + \mathrm{atan2}(\ \sin(\theta)\sin(d/R)\cos(\varphi_1),\ \cos(d/R)\text{-}\sin(\varphi_1)\sin(\varphi_2)\ ). \tag{5.3.4}$$

These formulas are incorporated by means of VBA functions, represented in listing A-6.

Intersection of two great circles defined by the arcs is a set of geographical pairs of coordinates that define the point where two great circles intersect.

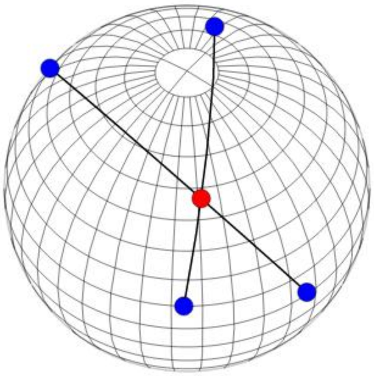


Figure 30. *Intersection of two great circles defined by the arcs*

A unit vector might be created from the center of the Earth to any point on its surface, say it is defined by De Cart 3d coordinates, say

$$\vec{e} = \{ex, ey, ez\} = \{\cos(\varphi)\cos(\lambda), \cos(\varphi)\sin(\lambda), \sin(\varphi)\}. \quad (5.3.5)$$

Obviously φ and λ then might be inverted in the following way:

$$\varphi = \operatorname{atan}2(ez, sqrt(ex^2 + ey^2)), \quad (5.3.6)$$

$$\lambda = -\operatorname{atan}2(-ey, ex). \quad (5.3.7)$$

The unit perpendicular (written in listing A-8) to the plane of any great circle is found with respect to the definition of vector multiplication of a pair of vectors in the following way:

$$\mathrm{P}(\overrightarrow{\mathrm{e1}},\overrightarrow{\mathrm{e2}}) = \frac{\overrightarrow{\mathrm{e1}} \text{ X } \overrightarrow{\mathrm{e2}}}{||\overrightarrow{\mathrm{e1}} \text{ X } \overrightarrow{\mathrm{e2}}||}, \quad (5.3.8)$$

where $\overrightarrow{\mathrm{e1}} \text{ X } \overrightarrow{\mathrm{e2}}$ is a vector cross-product of a pair of vectors:

$$\overrightarrow{\mathrm{e1}} \text{ X } \overrightarrow{\mathrm{e2}} = \{y_1 z_2 - y_2 z_1, z_1 x_2 - z_2 x_1, x_1 y_2 - y_1 x_2\} = \{x_v, y_v, z_v\}. \quad (5.3.9)$$

VBA vector cross-product of a pair of vectors is shown in listing A-9. This cross-product of a pair of vectors in spherical coordinates is done by means of (5.3.10)-(5.3.12). Robust VBA function for calculation of vector cross product of a pair of vectors, defined in spherical coordinates is shown in listing A-10 in the appendix of this thesis.

$$\begin{aligned} x_v = &-\sin(\varphi_1-\varphi_2)\sin((\lambda_1+\lambda_2)/2)\cos((\lambda_1-\lambda_2)/2) - \\ &-\sin(\varphi_1+\varphi_2)\cos((\lambda_1+\lambda_2)/2)\sin((\lambda_2-\lambda_1)/2) \end{aligned}, \tag{5.3.10}$$

$$\begin{aligned} y_v = &\sin(\varphi_1-\varphi_2)\cos((\lambda_1+\lambda_2)/2)\cos((\lambda_1-\lambda_2)/2) + \\ &+\sin(\varphi_1+\varphi_2)\sin((\lambda_1+\lambda_2)/2)\sin((\lambda_1-\lambda_2)/2) \end{aligned}, \tag{5.3.11}$$

$$z_v = \cos(\varphi_1)\cos(\varphi_2)\sin(\lambda_2-\lambda_1). \tag{5.3.12}$$

And $||\overrightarrow{e1} \text{ X } \overrightarrow{e2}||$ is the length of the vector cross product of the corresponding pair of vectors, which has the beginning at the zero point of the coordinate system (listing A-11):

$$||\overrightarrow{e1} \text{ X } \overrightarrow{e2}|| = ||\{x_v, y_v, z_v\}|| = \sqrt{x_v{}^2 + y_v{}^2 + z_v{}^2}\ . \tag{5.3.13}$$

In order to find the coordinates of intersections of great circles one should find the coordinates of the perpendicular to the plane surface, defined by the perpendiculars to the corresponding pair of great circles. In other words:

$$\overparen{\{\varphi_{1,1},\lambda_{1,1}\},\{\varphi_{1,2},\lambda_{1,2}\}} \cap \overparen{\{\varphi_{2,1},\lambda_{2,1}\},\{\varphi_{2,2},\lambda_{2,2}\}} = +-P(P(\overrightarrow{e_{1,1}},\overrightarrow{e_{1,2}}),P(\overrightarrow{e_{2,1}},\overrightarrow{e_{2,2}}))\,. \tag{5.3.14}$$

Which then are inverted to the spherical coordinates

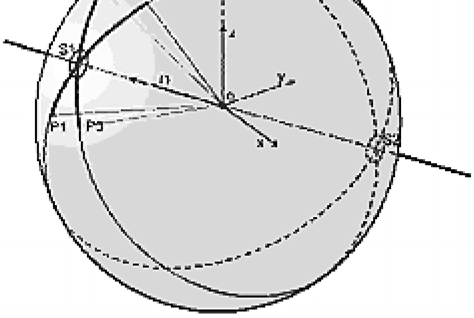


Figure 31. *Algorithm for finding the intersection point illustration*

So, the **formal algorithm** corresponding to (5.3.14) is simply as follows (listing A-12):

- **Find** a perpendicular to the first circle's plane
- **Find** a perpendicular to the second circle's plane
- **Find** both perpendiculars to the plane formed by the perpendiculars to the circles' planes
- **Make** an inverse transformation of the coordinates of the perpendiculars so as to find coordinates of points of intersection of circles.

Sailing Speed Reduction takes place during sailing of a vessel as a result of exogenous factors such as significant wave height and/or wave directions influence. Gruzinskiy and Khokhlov (1977) suggested a continuous function (5.3.15) for vessel speed loss estimation depending on such parameters as deadweight, initial speed, wave angle and finally significant wave height.

$$v = v_0 - h(0.745 - 0.245q_w)(1 - 1.35 \times 10^{-6} D v_0), \tag{5.3.15}$$

$$v_0 = \frac{v + h(0.745 - 0.245q_w)}{(1 + 1.35 \times 10^{-6} D h(0.745 - 0.245q_w))}, \tag{5.3.15*}$$

where v – is a reduced speed of a vessel in knots, v_0 – is a speed of a vessel in calm sea in knots, h – is a significant wave height in meters, q_w - is a wave angle in radians, is D - is a deadweight of a vessel.

According to Gruzinskiy and Khokhlov (1977) this formula is applicable for vessels with deadweight changing in range from 4 to 20 kilotons and the speed in range from 9 to 20 knots, the standard error of this formula is said not to exceed 0.5 knots. (5.3.15*) is used to find the initial speed given the reduced one.

The reduced speed is calculated by means of VBA function in the ARENA, represented in listing A-16.

Fuel consumption is usually given for the design speed of a vessel and thus whilst sailing it might well slightly vary as a result of changes of the engine speed of vessels. Formula (5.3.16) described in Norlund and Gribkovskaia (2013) provides the way to calculate real fuel consumption of a vessel during sailing.

$$FC(v) = FC(v_0)\left(\frac{v}{v_0}\right)^3, \tag{5.3.16}$$

where v_0 – is the design speed of a vessel, v – is the engine seed of a vessel measured in the same units as the design speed, $FC(v_0)$ – is the fuel consumption corresponding to the design speed of a vessel.

5.4 *Detailed description of the simulation model*

In this section we will provide the detailed description of the simulation tool from different prospectives such as GUI, sailing and routing algorithms, key parameters estimations and etc.

5.4.1 *Visual representation of the model in Arena*

The simulation model is contained in Model1.doe for Arena 13.5. Visual representation of the model in arena after having the installations and parameters constructed (by means of special VBA script run before the beginning of the simulation) looks as represented in Figure 32.

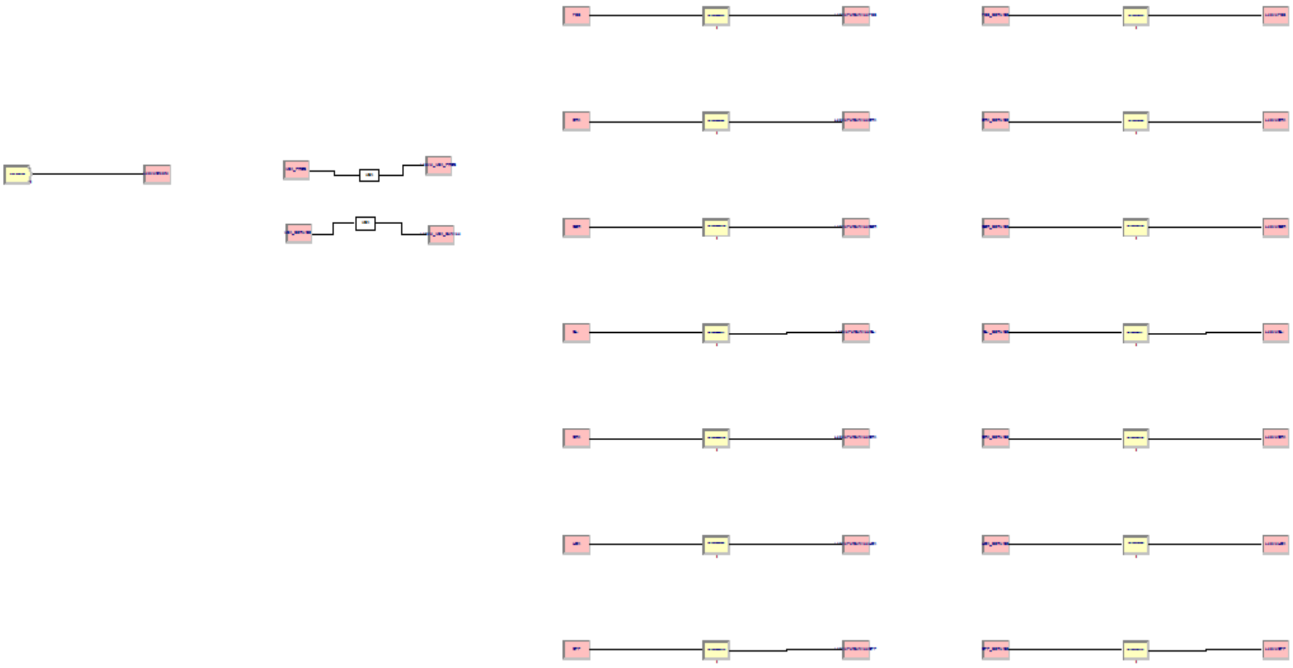


Figure 32. *A graphical representation of a Rockwell Arena model for the given problem*

VBA Script for cleaning the model from the previous simulation, building the "create" group of blocks and saving VBA-related group of blocks looks as shown in listing A-13.

Whilst installations data is read, the location specific code (listing A-14) is run in order to build the corresponding installation-specific groups of objects as depicted in Figure 32. Each node (destination, point, etc.) is represented by 6 blocks (stations and pick-stations blocks to implement arrivals and departures and 2 process blocks for a vessel to be serviced at a station properly, all of the assigned travelling and service times are incorporated in VBA code, connected with Arena software):

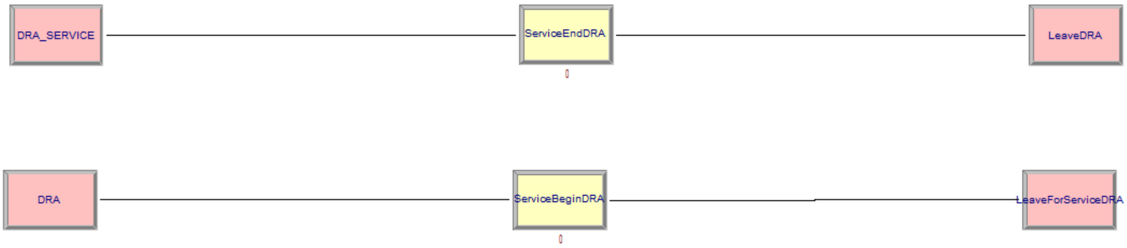


Figure 33. *A graphical representation of a Rockwell Arena model block at any of the installations*

When the vessel is departing from any station the routing VBA script is run (listing A-15), this script calculates travelling time with respect to the modelled weather conditions, whilst service time at the installation with respect to weather calculation is carried out in a separate service time estimating VBA script (listing A-17), which is run after LeaveForService pick station block (these VBA scripts also contain several data writing functions to output some key factors such as duration of routes (to find its distributions) and real departure (arrival, discharge) times versus planned to estimate service level and deviations from the expectations and other parameters).

Figure 34. *Possible geographical locations of an offshore point, a supply base and Installations*

5.4.2 Vessel travelling time modelling

The following exact algorithm is used for calculation of travelling times between any pair of geographical locations:

- **Get** geographical positions of the departure point and the destination point. Say φ_1, φ_2 are latitudes of these points, whilst λ_1, λ_2 are correspondingly longitudes of these points;
- **Calculate** spherical distance d_{ttl} between the pair of points by means of haversine spherical distance formula;
- **Calculate** the initial bearing θ of the vessel by means of the relevant formula.
- **Find** all points of intersections between the clusters on the way from (φ_1, λ_1) to (φ_2, λ_2), say they form a set *I*;
- **Set** time Δt so that at no point can the current vessel sail in 3 clusters of any weather parameter during this time interval Δt, ideally the greater the time satisfying this condition the better, since less iterations will be used to cover the given distance. In other words:

$$\begin{aligned}\Delta t = \max_t \{ & (\varphi_{j,k,i}, \lambda_{j,k,i}) \xrightarrow[v_{i,r} \times t, \theta_{j,k,i}]{} (\varphi_{j,k+1,i}, \lambda_{j,k+1,i}), \\ & \forall j \in J, k \in K_j, i \in V, [\exists ! \cup \boxtimes](\varphi_{j,x,i}, \lambda_{j,x,i}) \in I \}\end{aligned}, \tag{5.4.1}$$

where *J* is a set of possible voyages in the schedule, K_j is an ordered set of locations to be visited during voyage *j*, *I* is a set of points of intersections between the clusters of the current leg as has been mentioned above, *V* is a set of vessels, $A \xrightarrow[v \times t, \theta]{} B : R^2 \to R^2$ is a function describing travelling from point *A* with speed *v* and bearing θ for *t* time units, which ends up in point *B*;

- **Set** covered and current distances to zero, also set the initial time $d_{cvd} = 0, d_{crt} = 0, T = T_0$;
- **Set** $(\varphi_{crt}, \lambda_{crt}) = (\varphi_1, \lambda_1)$;
- **While** $d_{cvd} < d_{ttl}$, do:
- **Get** clusters $c_{p,(\varphi_{crt}, \lambda_{crt})}$ in which the vessel currently is (at $(\varphi_{crt}, \lambda_{crt})$) for all of the weather parameters $p \in P$;
- **Set** $$\tau = \min\{\Delta t, 3\left\lfloor \frac{T}{3} + 1 \right\rfloor - T\}; \tag{5.4.2}$$

- **Get** the weather parameters corresponding to the current clusters at time *T*: $w_{p,c_{p,(\varphi_{crt},\lambda_{crt})},T}$;

- **Calculate** the distance that would be covered if the weather clusters did not change during the ongoing τ time units (estimator of the distance to be covered during the following τ time units):

$$\begin{aligned}
&\hat{d}_{crt} = \tau \times v_{s,r} \\
&\hat{d}_{cvd} = d_{cvd} + \hat{d}_{crt} \\
&v_{s,r} = 1.852\left(\frac{v_{s,e}}{1.852} - w_{wh,c_{wh,(\varphi_{crt},\lambda_{crt})},T}(0.745 + 0.245 Q_{s,wd,c_{wd,(\varphi_{crt},\lambda_{crt})},T})(1 - 1.35\times 10^{-6} D_{W,s} \times \frac{v_{s,e}}{1.852})\right)
\end{aligned}, \qquad (5.4.3)$$

where $v_{s,r}$ is a real speed (speed of changing positions along the stationary coordinate system) of a vessel $s \in V$, $v_{s,e}$ is an engine speed of a vessel $s \in V$ both given in km/h, $w_{wh,c_{wh},t}$ is the significant wave height at cluster $c_{wh,T}$ at current time *T*, $Q_{s,wd,c_{wd,(\varphi_{crt},\lambda_{crt})},T}$ is an angle of waves against the direction of a vessel, $D_{W,s}$ is a deadweight of vessel $s \in V$;

- **Find** the expected geographical positions $(\hat{\varphi}_{nxt}, \hat{\lambda}_{nxt})$ of a vessel sailing by means of formulas (5.3.3) and (5.3.4) using the initial coordinates (φ_1, λ_1), initial bearing (θ) and the estimator of the expected covered distance $(\hat{d}_{cvd})$;

- **Get** clusters $\hat{c}_{p,(\hat{\varphi}_{nxt},\hat{\lambda}_{nxt})}$ in which the vessel would be at $(\hat{\varphi}_{nxt}, \hat{\lambda}_{nxt})$ for all of the weather parameters $p \in P$ if the vessel sailed $\hat{d}_{crt}$ distance units during the ongoing τ time units;

- **Get** the weather parameters corresponding to the current clusters at time $T + \tau$: $w_{p,c_{p,(\hat{\varphi}_{nxt},\hat{\lambda}_{nxt})},T+\tau}$;

- **Set** $\tau_c = \tau_l = d_{crt} = 0$;

- **While** $\tau_c \le \tau$;

- **Check** for which weather parameters $(\varphi_{crt}, \lambda_{crt})$ and $(\hat{\varphi}_{nxt}, \hat{\lambda}_{nxt})$ belong to different clusters;

- **For** the parameter p_{cc}, that has the border of the clusters crossed during the current τ (or in case several parameters cross their cluster borders during the current τ for the parameter that has the smallest distance from $(\varphi_{crt},\lambda_{crt})$ to the point of intersection). Say the intersection point is $(\varphi_{itn},\lambda_{itn})$:
- **Find** the distance d_{itn} d from (φ_1,λ_1) to $(\varphi_{itn},\lambda_{itn})$ with respect to the initial bearing θ by means of formulas (5.3.3) and (5.3.4);
- **Set** the distance left until $(\varphi_{itn},\lambda_{itn})$ as the current distance for the corresponding parameter: $d_{p_{cc},crt} = d_{itn} - d_{cvd}$;
- **Add** the time to cover $d_{p_{cc},crt}$ to τ_c: $\tau_c = \tau_c + \dfrac{d_{p_{cc},crt}}{v_{s,r}}$, $s \in V$;
- **Update** all weather parameters and clusters at $T+\tau_c$: $c_{p_{cc},(\varphi_{itn},\lambda_{itn})}$ and $w_{p_{cc},c_{p_{cc},(\varphi_{itn},\lambda_{itn})},T+\tau_c}$;
- **Add** $d_{p_{cc},crt}$ to d_{crt}: $d_{crt} = d_{crt} + d_{p_{cc},crt}$;
- **If** none of the weather parameters has the intersection between cluster points in the interval from $(\varphi_{crt},\lambda_{crt})$ to $(\varphi_{itn},\lambda_{itn})$ Then:
- **Set** $\tau_l = \tau - \tau_c$;
- **Add** the distance covered during τ_l to d_{crt}: $d_{crt} = d_{crt} + v_{s,r}\tau_l$;
- **Set** $\tau_c = \tau$;
- **End If**
- **End While**
- **Add** d_{crt} to d_{cvd}: $d_{cvd} = d_{cvd} + d_{crt}$;
- **Add** τ to T: $T = T + \tau$;
- **Update** the current position of a vessel $(\varphi_{crt},\lambda_{crt})$ by adding d_{cvd} to the initial position (φ_1,λ_1) with respect to the initial bearing θ by means of formulas (5.3.3) and (5.3.4);
- **End While**
- **Distract** the over sailed time and distance (if any is present):

$$T = T - \frac{d_{cvd} - d_{ttl}}{d_{cur}}\tau; \tag{5.4.4}$$

- **Calculate** final positions of a vessel (φ_2,λ_2);
- **Return** $\Delta T = T - T_0$ as the sailing time between the given pair of points.

However, it should be mentioned that this algorithm is rather hard both computationally and technically (finding and saving the intersection points, accurately calculating travelling times and distances to/from intersection points, considering simultaneous crossing of clusters' borders for several weather parameters, etc.) that is why we also suggest **a rather precise approximate delta-t algorithm for calculation of travelling times between any pair of geographical locations:**

- **Get** geographical positions of the departure point and the destination point. Say φ_1, φ_2 are latitudes of these points, whilst λ_1, λ_2 are correspondingly longitudes of these points;
- **Calculate** spherical distance d_{ttl} between the pair of points by means of haversine spherical distance formula;
- **Calculate** the initial bearing θ of the vessel by means of the relevant formula.
- **Set** time Δt as small as accurate you want to stay in terms of clusters' borders crossing.
- **Set** covered and current distances to zero, also set the initial time $d_{cvd} = 0, d_{crt} = 0, T = T_0$;
- **Set** $(\varphi_{crt}, \lambda_{crt})$;
- **While** $d_{cvd} < d_{ttl}$, do:
- **Get** clusters $c_{p,(\varphi_{crt},\lambda_{crt})}$ in which the vessel currently is (at $(\varphi_{crt}, \lambda_{crt})$) for all of the weather parameters $p \in P$;
- **Set** τ by means of (5.4.2);
- **Get** the weather parameters corresponding to the current clusters at time T: $w_{p,c_{p,(\varphi_{crt},\lambda_{crt})},T}$.
- **Calculate** the distance that is covered during τ considering that the clusters do not change during τ (changes in clusters might only take place once finishing sailing for τ time units from $(\varphi_{crt}, \lambda_{crt})$ in this algorithm) by means of (5.4.3);
- **Add** τ to T: $T = T + \tau$;
- **Update** the current position of a vessel $(\varphi_{crt}, \lambda_{crt})$ by adding d_{cvd} to the initial position (φ_1, λ_1) with respect to the initial bearing θ;
- **End While**
- **Distract** the over sailed time and distance (if any is present) by means of (5.4.4):

```
• Calculate final positions of a vessel $(\varphi_2, \lambda_2)$;
• Return $\Delta T = T - T_0$ as the sailing time between the given pair of points.
```

Implementation of the above algorithms is presented in listing A-15 (**v_inter** variable is used to switch between them so that if its value is true then the exact algorithm is used, whilst otherwise the approximate approach is carried out).

5.4.3 Vessel servicing time modelling

The following exact algorithm is used for calculation of service times at any of the installations or/and the supply base:

```
• Set $\tau_{crt}$ (current working time added during the current time interval), $\tau_{ttl}$ (total working time till the current moment), $\tau_{srv}$ (total real time till the current moment) and $\tau_{wtn}$ (total waiting time) equal to zero, $T_0$ - beginning of discharge time;
• Set $T = T_0$;
• Get $\tau_{isn}$ - time used for servicing a vessel of at the current installation in case of calm sea;
• Get clusters $c_{p,(\varphi_{crt}, \lambda_{crt})}$ in which the vessel currently is for all of the relevant weather type parameters $p \in P$;
• While $\tau_{ttl} < \tau_{isn}$:
• Set current hour of the day $h = 24\left(\frac{T}{24} - \left\lfloor \frac{T}{24} \right\rfloor\right)$
• Add waiting time with respect to the time windows (if any is present)
• If $h < h_{open}$ Then
    $\tau_{wtn} = \tau_{wtn} + h_{open} - h$
    $T = T + h_{open} - h$
• Else If $h > h_{close}$ Then
    $\tau_{wtn} = \tau_{wtn} + h_{open} + 24 - h$
    $T = T + h_{open} + 24 - h$
• End If
```

- **Set** $\Delta t = 3\left(\left\lfloor \frac{T}{3} \right\rfloor + 1\right) - T$, where T is a current time;
- **Get** the weather parameters corresponding to the current clusters at time T: $w_{p,c_{p,(\varphi_{crt},\lambda_{crt})},T}$;
- **Set** the corresponding to the current significant wave height utilized time of servicing of a vessel (listing A-18):
- **If** $w_{wh,c_{wh,(\varphi_{crt},\lambda_{crt})},T} \in (-\infty, 2.5)$ or $(\varphi_{crt}, \lambda_{crt}) = (\varphi_{fbs}, \lambda_{fbs})$ **Then**

$\tau_{crt} = \Delta t$

- **Else If** $w_{wh,c_{wh,(\varphi_{crt},\lambda_{crt})},T} \in [2.5, 3.5)$ **Then**

$$\tau_{crt} = \frac{\Delta t}{1.2}$$

- **Else If** $w_{wh,c_{wh,(\varphi_{crt},\lambda_{crt})},T} \in [3.5, 4.5)$ **Then**

$$\tau_{crt} = \frac{\Delta t}{1.3}$$

- **Else If** $w_{wh,c_{wh,(\varphi_{crt},\lambda_{crt})},T} \in [4.5, +\infty)$ **Then**

$\tau_{crt} = 0$;

- **End If**
- **Set** $\tau_{srv} = \tau_{srv} + \Delta t$ and $\tau_{ttl} = \tau_{ttl} + \tau_{crt}$;
- **Set** $T = T + \Delta t$;
- **End While**
- **Distract** the over used time and (if any is present):
- **If** $\tau_{srv} > \tau_{isn}$ **Then**

$$\tau_{srv} = \tau_{srv} - \tau_{crt} \frac{\left(\tau_{ttl} - \tau_{isn}\right)}{\Delta t};$$

- **End If**
- **Return** τ_{srv} as service time and τ_{wtn} as waiting for service time for the current installation at a given arrival time.

Implementation of the above algorithm is presented in listing A-17.

5.4.4 Routing algorithms and a posteriori improvements

The standard algorithm for routing of the vessels with respect to their schedule in discrete event-based simulation environment of the developed tool is as follows (note that in this section advanced and detailed mathematical notation will not be used, since these algorithms have mostly to do with management rather than calculus):

- **Begin** a replication;
- **Do:**
- **Simulate** weather;
- **While** the simulated weather lies inside acceptable bounds;
- **Create** instances of vessels;
- **Route** all vessels to their initial positions with assigned waiting times equal to the deviation of the corresponding departure time from the beginning of replication;
- **While** end of replication criterion is not met:
- **Wait** for the closest in time event of some vessels departure;
- **Route** the vessel to its destination with respect to the estimated sailing and waiting for arrival times (see section 5.4.2);
- **Wait** for recourse to become available and seize it;
- **Calculate** waiting and service times(see section 5.4.3);
- **Assign** waiting and service times to the recourse as its delay time set it to be released afterwards;
- **Write** all the relevant output parameters of the leg to the output file;
- **End While;**
- **Clear** all replication specific parameters and end replication.

Routing without a posteriori improvements (improvements' type 0 associated)

In this paragraph we provide a standard routing (finding the destination) algorithm with respect to the schedule being simulated.

- **Get** vessel id: vesID and its current step id: stepID = StepID(vesID);
- **Get** current location locID = LocationID(vesID, StepID);
- **Increment** the counter of visits of the current location Visit(locID)++;
- **Find** the destination id and **left-increment** the step counter of the vessel : destID = LocationID(vesID, ++StepID(veslID));

- **If** Name(locId)==“FBS” or Name(destId) == “FBS” (“FBS” is the supply base) **Then:**
- consider two great circles going firstly to “OFP” (offshore point) and then to the very destination when calculating sailing time and/or expected sailing time;
- **End If;**
- **Assign** the leg’s sailing, waiting for arrival and service times, calculated by means of algorithms, described in sections 5.4.2 and 5.4.3;
- **Route** the vessel with the assigned sailing, service and waiting (if applicable) times.
- **If** Name(destId) == “FBS” **Then:**
- **Assign** waiting time for the beginning of the next leg as Max{departureTime(vesID,destID) – departureTime(vesID,locID) – sailingTime – waitingArrivalTime – waitingServiceTime –serviceTime,0} ;
- **End If;**

Routing with waiting time and/or other deviations utilizations

In this section we will provide two routing (finding the destination) algorithms with respect to the schedule being simulated so as to utilize waiting times. The first algorithm (improvements of type 1) does not consider speed adjustments but rather just utilizes waiting slacks at the supply base (slacks between voyages utilization), which is however is hardly possible in practice, since the departures depend on the on-shore logistics; whilst the second algorithms adjusts speeds so as to minimize the deviations (improvements of type 2) from the expected departure times with respect to the available weather forecast taken into consideration so as to increase the service level without significant increase of fuel consumptions (or only tardiness (improvements of type 3) so as to increase the service level or only early departures (improvements of type 4) so as to reduce fuel consumptions as two additional alternatives).

The first algorithm is as follows:

- **Get** vessel id: vesID and its current step id: stepID = StepID(vesID);
- **Get** current location locID = LocationID(vesID, StepID);
- **Increment** the counter of visits of the current location Visit(locID)++;
- **Find** the destination id and **left-increment** the step counter of the vessel : destID = LocationID(vesID, ++StepID(veslID));
- **If** Name(locId)==“FBS” or Name(destId) == “FBS” (“FBS” is the supply base) **Then:**

- consider two great circles going firstly to “OFP” (offshore point) and then to the very destination when calculating sailing time;
- **End If;**
- **Assign** the leg’s sailing, service, and waiting for arrival times, calculated by means of algorithms, described in sections 5.4.2 and 5.4.3;
- **Route** the vessel with the assigned sailing and service times.

The second algorithm (and its alternatives) is as follows:

- **Get** vessel id: vesID and its current step id: stepID = StepID(vesID);
- **Get** current location locID = LocationID(vesID, StepID);
- **Increment** the counter of visits of the current location Visit(locID)++;
- **Find** the destination id and **left-increment** the step counter of the vessel : destID = LocationID(vesID, ++StepID(veslID));
- **If** Name(locId)==“FBS” or Name(destId) == “FBS” (“FBS” is the supply base) **Then:**
- consider two great circles going firstly to “OFP” (offshore point) and then to the very destination when calculating sailing time;
- **End If;**
- **Calculate** the expected leg’s sailing, waiting and service times by means of algorithms, described in sections 5.4.2 and 5.4.3 but using weather forecast instead of weather simulation;
- **If** Max{Abs(departureTime(vesID,locID) + ExpSailingTime + ExpServiceTime – departureTime(vesID,destID)),0} > Eps **Then****
- **Adjust** the leg’s speed so as to minimize the deviation from the expected departure time: vSpeedReduced = legDistance / (departureTime(vesID,destID)) – departureTime(vesID,locID)) – ExpServiceTime – ExpSailingTime + ScheduledSailingTime);
- **Use** formula (5.3.15*) with average forecasted WD and SWH to find vSpeedInitial corresponding to the reduced speed as it is in the previous step;
- **End If;**
- **Assign** the leg’s waiting and service times, calculated by means of algorithms, described in sections 5.4.2 and 5.4.3;

```
• Route the vessel with the assigned sailing, service and waiting for service and arrivals times.
• If Name(destId) == “FBS” Then:
• Assign waiting time for the beginning of the next leg as Max{departureTime(vesID,destID) – departureTime(vesID,locID) – sailingTime – waitingArrivalTime – waitingServiceTime –serviceTime,0} ;
• End If;
```

** Note that at this step “**If** Max{ (departureTime(vesID,locID) + ExpSailingTime + ExpServiceTime – departureTime(vesID,destID)),0} > Eps **Then”** might be used to utilize only deviations when vessels are delayed and/or “**If** Max{- (departureTime(vesID,locID) + ExpSailingTime + ExpServiceTime – departureTime(vesID,destID)),0} > Eps **Then**” might be used in order to get rid of early arrivals by reducing speed and thus reduce fuel costs associated.

Routing with voyages swapping (a posteriori improvement of type 5)

In this section we will provide a standard routing (finding the destination) algorithm with incorporated swaps of voyages between identical vessels.

```
• Get vessel id: vesID and its current step id: stepID = StepID(vesID);
• Get current location locID = LocationID(vesID, StepID);
• Increment the counter of visits of the current location Visit(locID)++;
• Find the destination id and left-increment the step counter of the vessel : destID = LocationID(vesID, ++StepID(veslID));
• If Name(locId)==“FBS” or Name(destId) == “FBS” (“FBS” is the supply base) Then:
• consider two great circles going firstly to “OFP” (offshore point) and then to the very destination when calculating sailing time;
• End If;
• Assign the leg’s waiting and service times, calculated by means of algorithms, described in sections 5.4.2 and 5.4.3;
• If Name(destId) == “FBS” Then:
• If waitingTime > 0 Then:
```

- **Route** the vessel to “FBS” with the assigned sailing, service times, whilst waiting time is set to 0;
- **Try Find** an identical vessel that is has not arrived to the supply base yet with the minimal departure time (say altID) in and case its departure from “FBS” time is earlier than those of vesID, **swap** the remaining voyages between vessels altID and vesID and **reassign** the waiting times;
- **End If;**
- **End If;**
- **Route** the vessel with the assigned sailing, service and waiting times.
- **If** Name(destId) == “FBS” **Then:**
- **Assign** waiting time for the beginning of the next leg as Max{departureTime(vesID,destID) – departureTime(vesID,locID) – sailingTime – waitingArrivalTime – waitingServiceTime –serviceTime,0} ;
- **End If;**

Routing with mixed a posteriori improvements (a posteriori improvement of type 6)

In this section we combine improvements of types 2 and 5:

- **Get** vessel id: vesID and its current step id: stepID = StepID(vesID);
- **Get** current location locID = LocationID(vesID, StepID);
- **Increment** the counter of visits of the current location Visit(locID)++;
- **Find** the destination id and **left-increment** the step counter of the vessel : destID = LocationID(vesID, ++StepID(veslID));
- **If** Name(locId)==“FBS” or Name(destId) == “FBS” (“FBS” is the supply base) **Then:**
- consider two great circles going firstly to “OFP” (offshore point) and then to the very destination when calculating sailing time;
- **End If;**
- **Calculate** the expected leg’s waiting and service times by means of algorithms, described in sections 5.4.2 and 5.4.3 but using weather forecast instead of weather simulation;
- **If** Name(destId) != “FBS” and Max{Abs(departureTime(vesID,locID) + ExpSailingTime + ExpServiceTime – departureTime(vesID,destID)),0} > Eps **Then****
- **Adjust** the leg’s speed so as to minimize the deviation from the expected departure time: vSpeedReduced = legDistance / (departureTime(vesID,destID)) –

departureTime(vesID,locID)) – ExpServiceTime – ExpSailingTime + ScheduledSailingTime);

- **Use** formula (5.3.15*) with average forecasted WD and SWH to find vSpeedInitial corresponding to the reduced speed as it is in the previous step;
- **End If;**
- **Assign** the leg's waiting and service times, calculated by means of algorithms, described in sections 5.4.2 and 5.4.3;
- **If** Name(destId) == "FBS" **Then:**
- **Assign** waiting time for the beginning of the next leg as waitingTime = Max{departureTime(vesID,destID) – departureTime(vesID,locID) – sailingTime – serviceTime,0} ;
- **If** waitingTime > 0 **Then:**
- **Route** the vessel to "FBS" with the assigned sailing, service times, whilst waiting time is set to 0;
- **Try Find** an identical vessel that is has not arrived to the supply base yet with the minimal departure time (say altID) in and case its departure from "FBS" time is earlier than those of vesID, **swap** the remaining voyages between vessels altID and vesID and **reassign** the waiting time with respect to the new schedule of the vessel;
- **End If;**
- **End If;**
- **Route** the vessel with the assigned sailing, service and waiting times.

5.4.5 Assumptions and simplifications

Several simplifications are assumed so far: stochastic processes of significant wave height and wave directions are assumed to be ARIMA stochastic processes, which describe them in a rather precise way, even though these processes might depend on other parameters in addition to the lagged values of the corresponding time series and the lagged values of the residuals of the corresponding model. Service time at the installations is assumed to have a discrete conditional distribution depending on the current wave height, whereas, this process in reality is a process of a more sophisticated nature and thus should be addressed in more details as a separate research issue

6. Evaluations of schedules

In this chapter we will provide estimations of robustness for a given set of schedules with respect to such parameters as estimates of mathematical expectations, standard deviations, margins of error and confidence intervals of such parameters as service levels, tardiness, deviations, fuel consumption and fuel costs. Afterwards schedules will be ranked by means of multicriteria ranking algorithm (TOPSIS).

6.1 Output and key factors analysis

In this section such output parameters as distributions of sailing times between any pair of nodes as well as average tardiness, deviations and confidence intervals of departures, arrivals and discharges for the schedule, service levels, fuel consumption levels and/or corresponding to them costs. All data is tested basing on a great number of replications. Such key factors as duration distributions for any pair of nodes and service level connected parameters are output into the text files output.csv and studied by means of some pieces of external software such as Statistica 8.0, SPSS 18.0, Wolfram Mathematica 9.0 and/or problem specific C# code. C# application for "cleaning outputs" and calculating means, standard deviations, margins of errors and confidence intervals for service level, tardiness over the replications and fuel costs is run automatically after the end of the simulation.

6.1.1 Distributions of travelling times between the nodes analysis

The first group of factors to be addressed are trip durations distributions (from which route durations distributions might well be derived analytically).

Since this analysis is not in the core of this research, we without loss of generality address a link between just one pair of nodes (this might easily be extent to all of the links by means of e.g. wolfram Mathematica code). We will address the link between Sleipner and Heimdal (direction from Sleipner to Heimdal) for a vessel Foresight (leg speed is assumed to be 12 knots, deadweight 4847 tons). A sample of durations data looks as represented in Table 19.

Sleipner	Heimda	6.148937
Sleipner	Heimdal	6.275047
Sleipner	Heimdal	6.224324
Sleipner	Heimdal	6.310443
Sleipner	Heimdal	6.310525
Sleipner	Heimdal	6.460192

Table 19. *Travelling times for a particular vessel between a particular pair of nodes*

As one can see in Figures 35 and 36 there is neither autocorrelation nor partial correlation present for the given time series, thus observations might well be concluded to be independent.

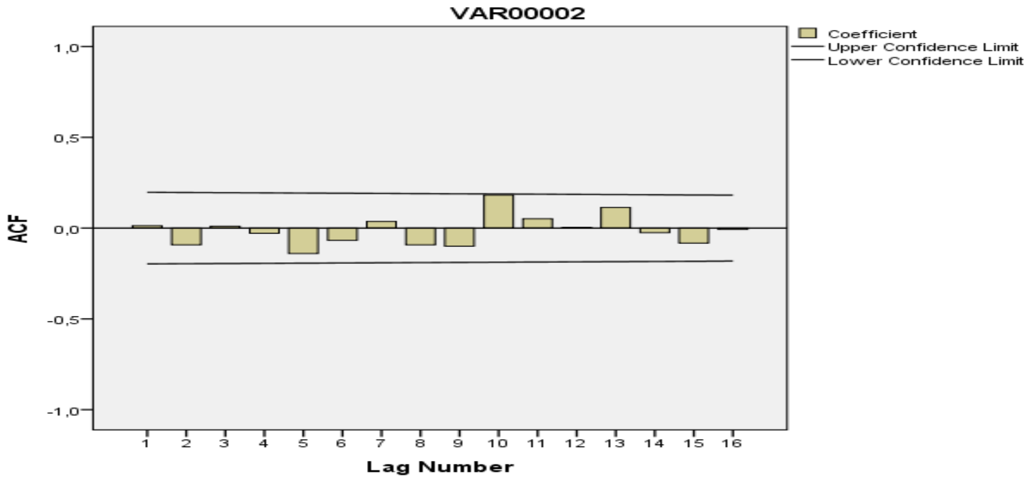


Figure 35. *Autocorrelation analysis of travelling times between some pair of nodes for a particular vessel*

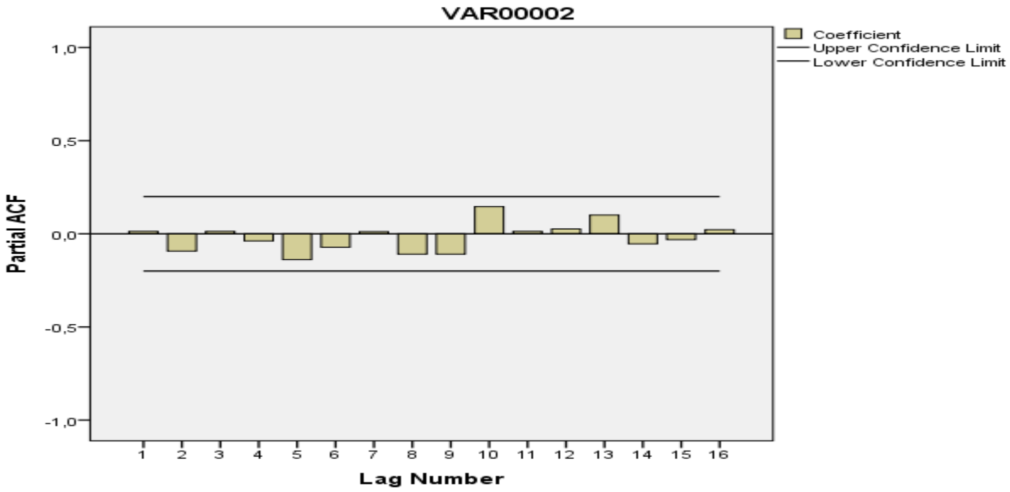


Figure 36. *Partial autocorrelation analysis of travelling times between some pair of nodes for a particular vessel*

Thus, the fit test might be addressed. By means of Chi-Square test the normality assumption of the data might not be rejected. The data is distributed with $N(\mu,\sigma) = N(6.40, 0.15)$ normal distribution. In a more general case T-distribution might be addressed for such pieces of data.

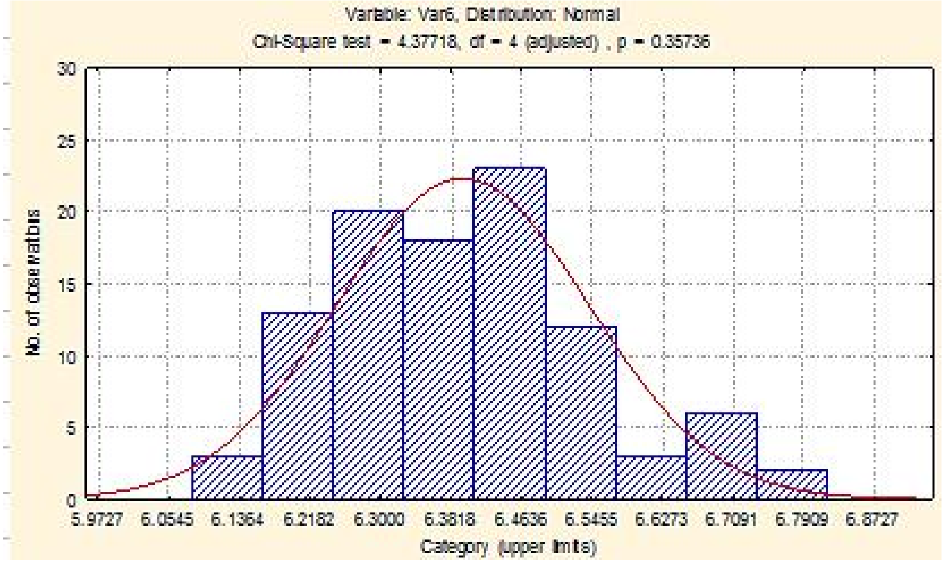


Figure 37. *Distribution analysis of travelling times between some pair of nodes for a particular vessel*

Supposing that durations for all links are normal with some parameters (which is without loss of generality considered to be true) $N(\mu_1,\sigma_1),\ldots,N(\mu_n,\sigma_n)$ and these durations are independent by the assumption of a given model (described above), the duration of any route might be calculated analytically as: $N(\mu_1+\ldots+\mu_n, \sqrt{\sigma_1^2+\ldots+\sigma_n^2})$ where n is the length of the route (number of arcs in the route). This lets us incorporate time buffers (slack) into the optimization model for creating schedules of the vessels so as to achieve both high utilization of time and high service level of the schedules afterwards. We only provide a rather brief overview of the leg-times distributions, since this topic is out of core of the problem of our research; however the tool developed might easily be used for the detailed investigation of this issue, since it has all the necessary in-built functionality for capturing travel durations of any vessel between any pair of locations. This sort of statistics is being written to the output file.

6.1.2 Quality of schedules key factor analysis

Several measures of quality (**robustness versus fuel consumption**) of schedules might be addressed for our problem. These measurers might be represented by such parameters as average tardiness and deviations of departures, arrivals and discharges times for schedules or service level. Yet another group of parameters to be addressed are those related to fuel consumption levels and/or corresponding to them costs.

Parameter 1 (Service level estimator of a given schedule for a single replication):

$$SS = \frac{1}{m}\sum_{i=1}^{m} \max(0, sign(h - t_i)). \tag{6.1.1}$$

Parameter 2 (Service level estimator of voyages of a given schedule for a single replication):

$$SV = \frac{1}{m}\sum_{i=1}^{m} \max(0, sign(p_{v_{i,j}} - t_i)),\ j = \overline{1, v}. \tag{6.1.2}$$

Parameter 3 (Completion of a schedule in time for a single replication):

$$PS = \max(0, sign(h - t_{end})). \tag{6.1.3}$$

Parameter 4 (Completion of voyages of a schedule in time for a single replication):

$$PV = \frac{1}{v}\sum_{j=1}^{v} \max(0, sign(p_{v_{end,j}} - t_{end,j})). \tag{6.1.4}$$

Parameter 5 (Final tardiness of a schedule for a single replication):

$$TSs = \max(0, (h - t_{end})). \tag{6.1.5}$$

Parameter 6 (Final deviation of a schedule for a single replication):

$$DSs = | h - t_{end} |. \tag{6.1.6}$$

Parameter 7 (Average final tardiness of voyages of a schedule for a single replication):

$$TSv = \frac{1}{v}\sum_{j=1}^{v} \max(0, p_{v_{end,j}} - t_{end,j}). \tag{6.1.7}$$

Parameter 8 (Average final deviation of voyages of a schedule for a single replication):

$$DSv = \frac{1}{v}\sum_{j=1}^{v} | p_{v_{end,j}} - t_{end,j} |. \tag{6.1.8}$$

Parameter 9 (Average tardiness estimator of a given schedule for a single replication):

$$TST = \frac{1}{m}\sum_{i=1}^{m} (\max(t_i - p_i, 0)). \tag{6.1.9}$$

Parameter 10 (Average deviation estimator for a given schedule for a single replication):

$$TSD = \frac{1}{m}\sum_{i=1}^{m} | t_i - p_i |, \tag{6.1.10}$$

where m is the number of scheduled visits, t_i are moments of actual visit to location i (arrivals, departures or discharges at them), where h is the planning horizon (replication length), p_i are times of scheduled departures at step *i*, $p_{v_{i,j}}$ are times of endings of voyage *j*, to which the visit *i* belongs, t_{end} is the time of the actual completion of the schedule, $t_{end,j}$ is the time of actual completion of voyage *j* from the schedule, $i = \overline{1,m}, j \in \overline{1,v}$.

Parameter 11 (Total level of fuel consumptions of a certain type):

$$FC_j = \sum_{i=1}^{m} t_{i,j} (fc)_j , j \in \{FC_{base}, FC_{installation}, FC_{sailing}, FC_{total}\}, \tag{6.1.11}$$

$$(fc)_{total} = \sum_{j \in \{FC_{base}, FC_{installation}, FC_{sailing}\}} (fc)_j . \tag{6.1.12}$$

Parameter 12 (Fuel consumption costs):

$$FCOST_j = MC \times FC_j , j \in J \equiv \{FC_{base}, FC_{installation}, FC_{installation}, FC_{total}\}, \tag{6.1.13}$$

where m is the number of scheduled visits, $t_{i,j}$ are durations of service at some point *i* or durations of sailing to point *i*, $fc_j , j \in \{FC_{base}, FC_{installation}, FC_{installation}\}$ are fuel consumptions per time unit at the corresponding locations, *MC* are costs of fuel per ton, which are assumed to be constant (though in reality might slightly fluctuate even on a weekly-based horizon).

In order to estimate **robustness** of the whole schedule rather than just one replication (and to compare different schedules in a fair way in case this is necessary) service level for the aggregated over replications data will be addressed as well as tardiness and deviations of arrival, discharge and departure times, fuel consumptions of all types and the corresponding to them costs for the aggregated over replications data (note that due to Central Limit Theorem aggregated tardiness, deviations, fuel consumption and fuel costs may be assumed to be normally distributed at least from some *k*). Also **note** that for those parameters that are relevant for every visit in the replication batching-meaning technique with one large batch will be applied so as to get rid of possible bias of the confidence intervals and these confidence intervals are in a way an upper bound of possible confidence intervals for these parameters, whilst for those parameters that are only calculated one time per replication we consider the standard deviation based on the deviations of the outcomes of every replication around the mean values of the corresponding parameters and thus the confidence intervals for their means might well be a way tighter that in reality (biased). One should keep that in mind, when reading the analysis of the results and do not compare confidence intervals of different parameters of the same schedule but rather than that compare confidence intervals of the same parameters of different schedules in case this is a matter of a detailed analysis. Estimates of mathematical expectation of different parameters are unbiased and thus might be a reliable foundation for further multicriteria ranking of the schedules.

Parameter 1 (Service level for the whole schedule):

$$\widehat{P} = E\{SS\} = \frac{1}{m \times k}\left(\sum_{i=1}^{k}\sum_{j=1}^{m}\max(0, sign(h - t_{i,j}))\right) - \tag{6.1.14}$$

– mathematical expectation estimator of service level for a given schedule over the replications;

$$s\{SS\} = \sqrt{\frac{\widehat{P}(1-\widehat{P})}{m \times k}} - \tag{6.1.15}$$

– standard deviation estimator of service level for a given schedule over the replications;

$$ME\{SS\} = z_{\alpha/2}\frac{s\{SS\}}{\sqrt{m \times k}} - \tag{6.1.16}$$

– margin of error estimator of service level for a given schedule over the replications.

Parameter 1.1 (Service level for any subset of a schedule (including visits of a particular installation only)):

$$\widehat{P} = E\{SS_{SET}\} = \frac{1}{\|SET\| \times k}\left(\sum_{i=1}^{k}\sum_{j \in SET}\max(0, sign(h - t_{i,j}))\right) - \tag{6.1.17}$$

– mathematical expectation estimator of service level for a given subset of installations over the replications;

$$s\{SS_{SET}\} = \sqrt{\frac{\widehat{P}(1-\widehat{P})}{\|SET\| \times k}} - \tag{6.1.18}$$

– standard deviation estimator of service level for a given subset of installations over the replications;

$$ME\{SS_{SET}\} = z_{\alpha/2}\frac{s\{SS_{SET}\}}{\sqrt{\|SET\| \times k}} - \tag{6.1.19}$$

– margin of error estimator of service level for a given subset of installations over the replications.

Note that this parameter (as well as all of the parameters below recalculated for some subset of a schedule) may be used in order to find bottlenecks of the schedule.

Parameter 2 (Service level for voyages of a schedule):

$$\widehat{P} = E\{SV\} = \frac{1}{m \times k}\left(\sum_{i=1}^{k} \sum_{j=1}^{m} \max(0, sign(v_{i,s} - t_{i,j})) \right), s = \overline{1, v} - \tag{6.1.20}$$

– mathematical expectation estimator of service level for voyages of a given schedule over the replications;

$$s\{SV\} = \sqrt{\frac{\widehat{P}(1-\widehat{P})}{m \times k}} - \tag{6.1.21}$$

– standard deviation estimator of service level for voyages of a given schedule over the replications;

$$ME\{SV\} = z_{\alpha/2} \frac{s\{SV\}}{\sqrt{m \times k}} - \tag{6.1.22}$$

– margin of error estimator of service level for voyages of a given schedule over the replications.

Parameter 3 (Percentage of performed schedules):

$$\widehat{P} = E\{PS\} = \frac{1}{k}\left(\sum_{i=1}^{k} \max(0, sign(h - t_{i,end})) \right) - \tag{6.1.23}$$

– mathematical expectation estimator of the number of performed schedules over the replications;

$$s\{PS\} = \sqrt{\frac{\widehat{P}(1-\widehat{P})}{k}} - \tag{6.1.24}$$

– standard deviation estimator of the number of performed schedules over the replications;

$$ME\{PS\} = z_{\alpha/2} \frac{s\{PS\}}{\sqrt{k}} - \tag{6.1.25}$$

– margin of error estimator of the number of performed schedules over the replications.

Parameter 4 (Percentage of performed voyages):

$$\widehat{P} = E\{PV\} = \frac{1}{k \times v}\left(\sum_{i=1}^{k} \sum_{j=1}^{v} \max(0, sign(v_{end,j} - t_{i,j,end})) \right) - \tag{6.1.26}$$

– mathematical expectation estimator of the number of performed schedules over the replications;

$$s\{PV\} = \sqrt{\frac{\widehat{P}(1-\widehat{P})}{k \times v}} - \tag{6.1.27}$$

– standard deviation estimator of the number of performed schedules over the replications;

$$ME\{PV\} = z_{\alpha/2}\frac{s\{PV\}}{\sqrt{k \times v}} - \tag{6.1.28}$$

– margin of error estimator of the number of performed schedules over the replications.

Parameter 5 (Final tardiness of a schedule):

$$E\{TSs\} = \frac{1}{k}\left(\sum_{i=1}^{k}\max(0, h - t_{i,end})\right) - \tag{6.1.29}$$

– mathematical expectation estimator of the number of performed schedules over the replications;

$$s\{TSs\} = \sqrt{\frac{1}{k-1}\sum_{j=1}^{k}\left(\widehat{E}\{TSs\} - TSs_j\right)^2} - \tag{6.1.30}$$

– standard deviation estimator of the number of performed schedules over the replications;

$$ME\{TSs\} = z_{\alpha/2}\frac{s\{TSs\}}{\sqrt{k}} - \tag{6.1.31}$$

– margin of error estimator of the number of performed schedules over the replications.

Parameter 6 (Final deviation of a schedule):

$$E\{DSs\} = \frac{1}{k}\left(\sum_{i=1}^{k}| h - t_{i,end} |\right) - \tag{6.1.32}$$

– mathematical expectation estimator of the number of performed schedules over the replications;

$$s\{DSs\} = \sqrt{\frac{1}{k-1}\sum_{j=1}^{k}\left(\widehat{E}\{DSs\} - DSs_j\right)^2} - \tag{6.1.33}$$

– standard deviation estimator of the average number of performed schedules over the replications;

$$ME\{DSs\} = z_{\alpha/2}\frac{s\{DSs\}}{\sqrt{k}} - \tag{6.1.34}$$

– margin of error estimator of the average number of performed schedules over the replications.

Parameter 7 (Final average tardiness of voyages of a schedule):

$$E\{TSv\} = \frac{1}{k}\left(\frac{1}{v}\sum_{i=1}^{k}\sum_{j=1}^{v}\max(0, p_{v_{end,j}} - t_{end,j})\right) - \tag{6.1.35}$$

– mathematical expectation estimator of the number of performed schedules over the replications;

$$s\{TSv\} = \sqrt{\frac{1}{k-1}\sum_{j=1}^{k}\left(\widehat{E}\{TSs\} - TSv_j\right)^2} - \qquad (6.1.36)$$

– standard deviation estimator of the number of performed schedules over the replications;

$$ME\{TSv\} = z_{\alpha/2}\frac{s\{TSv\}}{\sqrt{k}} - \qquad (6.1.37)$$

– margin of error estimator of the number of performed schedules over the replications.

Parameter 8 (Final average deviation of voyages of a schedule):

$$E\{DSv\} = \frac{1}{k}\left(\frac{1}{v}\sum_{i=1}^{k}\sum_{j=1}^{v}| p_{v_{end,j}} - t_{end,j} |\right) - \qquad (6.1.38)$$

– mathematical expectation estimator of the average number of performed schedules over the replications;

$$s\{DSv\} = \sqrt{\frac{1}{k-1}\sum_{j=1}^{k}\left(\widehat{E}\{DSv\} - DSv_j\right)^2} - \qquad (6.1.39)$$

– standard deviation estimator of the number of performed schedules over the replications;

$$ME\{DSv\} = z_{\alpha/2}\frac{s\{DSv\}}{\sqrt{k}} - \qquad (6.1.40)$$

– margin of error estimator of the average number of performed schedules over the replications.

Parameter 9 (Average tardiness of visits):

$$\widehat{E}\{T\} = \frac{1}{k \times m}\sum_{j=1}^{m}\sum_{i=1}^{k}\max(p_{i,j} - t_{i,j}, 0) - \qquad (6.1.41)$$

– mathematical expectation estimator of tardiness for a given schedule over the replications;

$$s\{T\} = \sqrt{\frac{1}{m-1}\sum_{j=1}^{m}\left(\widehat{E}\{T\} - \frac{1}{k}\sum_{i=1}^{k}\max(p_{i,j} - t_{i,j}, 0)\right)^2} - \qquad (6.1.42)$$

– standard deviation estimator of tardiness for a given schedule over the replications;

$$ME\{T\} = t_{m-1,\alpha/2}\frac{s\{T\}}{\sqrt{m}} - \qquad (6.1.43)$$

– margin of error estimator of tardiness for a given schedule over the replications.

Parameter 10 (Average deviations of visits):

$$\widehat{E}\{D\} = \frac{1}{k \times m}\sum_{j=1}^{m}\sum_{i=1}^{k}| p_{i,j} - t_{i,j} | - \qquad (6.1.44)$$

– mathematical expectation estimator of deviations for a given schedule over the replications;

$$s\{D\}=\sqrt{\frac{1}{m-1}\sum_{j=1}^{m}\left(\widehat{E}\{T\}-\frac{1}{k}\sum_{i=1}^{k}|\,p_{i,j}-t_{i,j}\,|\right)^{2}}\ - \qquad (6.1.45)$$

– standard deviation estimator of deviations for a given schedule over the replications;

$$ME\{D\}=t_{m-1,\alpha/2}\frac{s\{D\}}{\sqrt{m}}- \qquad (6.1.46)$$

– margin of error estimator of deviations for a given schedule over the replications, where *m* is the number of scheduled visits, *k* is the number of replication, $t_{i,j}$ are times of actual visit of *j* at replication *i* (departures from it), where *h* is the planning horizon (replication length), $p_{i,j}$ are times of scheduled departures from $j\in\overline{1,m}$ at replication $i\in\overline{1,k}$, *SET* is a set of indices of installations of interest for calculating their joint service level. ||*|| is the cardinality of set operator, $p_{v_{i,j}}$ are times of endings of voyage *j*, to which the visit *i* belongs, t_{end} is the time of the actual completion of the schedule, $t_{end,j}$ is the time of actual completion of voyage *j* from the schedule, $i=\overline{1,m},\ j\in\overline{1,v}$.

Parameter 11 (Fuel consumptions at the base, installations, during sailing and in total):

$$\widehat{E}\{FC_j\}=\frac{1}{k}\sum_{r}^{k}\sum_{i=1}^{m}t_{i,j,r}(fc)_j,\ j\in\{FC_{base},FC_{installation},FC_{installation},FC_{total}\}- \qquad (6.1.47)$$

– mathematical expectation estimator of fuel consumption for a given schedule over the replications;

$$s\{FC_j\}=\sqrt{\frac{1}{k-1}\sum_{r=1}^{k}\left(\widehat{E}\{FC_j\}-\sum_{i=1}^{m}t_{i,j,r}(fc)_j\right)^{2}}\ ,j\in\{FC_{base},FC_{installation},FC_{installation},FC_{total}\}- \qquad (6.1.48)$$

– standard deviation estimator of fuel consumption for a given schedule over the replications;

$$ME\{FC_j\}=t_{k-1,\alpha/2}\frac{s\{FC_j\}}{\sqrt{k}}- \qquad (6.1.49)$$

– margin of error estimator of fuel consumption for a given schedule over the replications.

Parameter 12 (Fuel consumption costs):

$$\widehat{E}\{FCOST_j\}=MC\times\widehat{E}\{FC_j\},\ j\in J\equiv\{FC_{base},FC_{installation},FC_{sailing},FC_{total}\}- \qquad (6.1.50)$$

– mathematical expectation estimator of fuel costs for a given schedule over the replications;

$$s\{FCOST_j\}=\sqrt{\frac{1}{k-1}\sum_{r=1}^{k}\left(\widehat{E}\{FCOST_j\}-FCOST_{j,r}\right)^{2}}\ ,j\in\{FC_{base},FC_{installation},FC_{installation},FC_{total}\}- \qquad (6.1.51)$$

– standard deviation estimator of fuel costs for a given schedule over the replications;

$$ME\{FCOST_j\} = t_{k-1,\alpha/2} \frac{s\{FCOST_j\}}{\sqrt{k}} - \qquad (6.1.52)$$

– margin of error estimator of fuel consumption for a given schedule over the replications, where *m* is the number of scheduled visits, *k* is the number of replication, $t_{i,j}$ are durations of service of type *j* and/or sailing at/to *i-th* location during *r-th* replication*,* $fc_j, j \in \{FC_{base}, FC_{sailing}, FC_{installation}, FC_{total}\}$ are fuel consumptions per time unit at the corresponding locations, *MC* are costs of fuel per ton, which are assumed to be constant (though in reality these market prices might slightly fluctuate even on a weekly-based horizon).

Estimates for these parameters' estimators for the whole schedule might for example look as follows:

E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.917084378	0.00398516	0.000112882	0.916971496	0.91719726
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.584761166	0.020639578	0.001694414	0.583066752	0.58645558
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.692982456	0.043200651	0.007930379	0.685052077	0.700912835
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.685964912	0.019440284	0.001595957	0.684368955	0.68756087
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
22.90862549	4.548470898	0.834966528	22.07365896	23.74359201
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
23.2450482	4.539576865	0.833333843	22.41171435	24.07838204
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
21.94367663	12.26688815	10.75240155	11.19127508	32.69607817
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
22.0153046	12.30692941	10.78749925	11.22780535	32.80280386
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
16.94398097	9.881551523	3.423782924	13.52019804	20.36776389
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
17.54400799	10.68500475	3.702165265	13.84184273	21.24617326
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
17.03379432	9.827591147	3.405086608	13.62870771	20.43888093
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
17.62914106	10.63764405	3.68575562	13.94338544	21.31489669
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
18.46607916	9.793738447	3.393357246	15.07272191	21.8594364
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
19.57832735	10.983246	3.805500585	15.77282676	23.38382793
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1241.173207	111.9450688	20.54984797	1220.623359	1261.723055
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
69.38426362	6.051843219	1.110941817	68.2733218	70.49520543
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
744.8065904	66.88080197	12.2773636	732.5292269	757.083954
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2055.364061	184.8349901	33.93031053	2021.43375	2089.294371
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
10276820.3	924174.9505	169651.5526	10107168.75	10446471.86

Table 20. *Estimates of key parameters example*

These estimates are achieved by means of C# code for analyzing the output of the model (see listing A-20). The reason why external C# code is used is that at first ARENA has a limited memory and by doing so we try to escape additional problems and at second C# code is commonly assumed to work much faster than VBA, moreover this gives some flexibility for both future researchers and users of the simulation tool since by means of replacing analyze.exe with their own *.exe file they can calculate other possible service parameters or carry out other sort of statistical data analysis and they do not have to know VBA scripts for ARENA but rather use any of familiar programming language. This code is automatically run after the end of simulation, which is simply achieved by procedure in VBA of the model, written in listing A-19.

6.1.3 Multicriteria choice

As it has been already noticed in the introductory chapters of the given thesis multicriteria ranking of schedules becomes vitally important. Decision making is a part of our daily lives. In decision support science, decision making problems based on multiple parameters are classified into the following categories: multi attribute decision making (MADM) and multi objective decision making (MODM). The major difference of the two classes is the existence of predetermined alternatives or their absence. MODM deals with optimization problems in which several objective functions should be satisfied, while MADM is associated with the problems in which alternatives have been predetermined. It means that making preference decisions (e.g., evaluation, prioritization, and selection) is made over the available alternatives that are characterized by multiple, usually conflicting, attributes. MADM methods are widely used for real world problems. In our case MADM is the very problem to be addressed since we do evaluation of real schedules basing on the simulation tool. There exist different methods of MADM multicriteria ranking of data including ELECTRE TRI, Utility Function Based Approaches, TOPSIS, MAVT, Outranking Approaches, Tree Based Approaches, LINMAP and others. These methods are different in the types of information that they need: for example, ELECTRE and TOPSIS methods cannot be used in a case when ideal alternatives and weights of criteria are not available, whilst LINMAP might be used in such cases, and etc. In this thesis we will address TOPSIS algorithm for schedules multicriteria ranking, since it does not only scale the schedules by weighting the parameters but also compares every schedule to the possible ideal schedule and in such terms combines benefits of ELECTRE and Utility Function Based Approaches. However we will describe all three of these approaches.

ELECTRE (ELimination Et Choix Traduisant la Realite)

ELECTRE method was developed by a group of French scientists headed by Professor B.Rua. Currently, a number of methods of family ELECTRE are available. In this method, evaluation of each alternative is not absolute, but relative (compared to the alternative) and thus alternatives must be compared pair wisely with respect to all of the criteria, what makes the whole process computationally sophisticated. Thus, ELECTRE method is based on pairwise comparison of alternatives, however with no predetermined quantitative measure of quality of any of the alternatives (so called utility function), but rather than that a condition of superiority of one alternative over another is used. Suppose that *N* scales of criteria weights are set and alternatives have estimates of the criteria. So as to determine the superiority of alternative *A* over alternative *B* two indices of agreement and disagreement are defined (agreement and disagreement with the hypothesis that alternative *A* is superior over alternative *B*). In this paper, we review the following method of constructing indices of agreement and disagreement :

The hypothesis of the superiority of alternative *A* over alternative *B* is shown below, where set I consists of *N* criteria, divided into three subsets:

- I^+ – a subset of the criteria by which *A* is preferable to *B*;
- $I^=$ – a subset of the criteria by which *A* is equivalent to *B*;
- I^- – a subset of the criteria by which *B* is preferable to *A*.

Index of agreement α_{AB} is calculated basing on the criteria weights. In the method used, index is defined as the sum of the weights of criteria subsets I^+ and $I^=$ divided by the total sum of the weights:

$$\alpha_{AB} = \frac{\sum_{i \in I^+, I^=} w_i}{\sum_{i=1}^{N} w_i}, 0 < \alpha_{AB} < 1, \qquad (6.1.53)$$

Whilst index of disagreement with the hypothesis of the superiority of *A* over *B* is determined on the basis of the "controversial" criterion, in other words the criterion by which *B* is most superior over *A*.

$$\beta_{AB} = \max_{i \in I^-} \frac{w_i \left| z^i{}_B - z^i{}_A \right|}{d_i \sum_{j=1}^{N} w_j}, 0 < \beta_{AB} < 1, \qquad (6.1.54)$$

where $z^i{}_A$, $z^i{}_B$ are estimates of alternatives *A* and *B* based on i-th criterion; d_i is the scale length of i-th criterion, w_j is the weight of j-th criterion.

The Imposed indices are used to construct matrices of indices of agreement and disagreement for the given alternatives. Binary relation of superiority of one alternative over the other alternative is given by the levels of agreement and disagreement. If $\alpha_{AB} > \mathrm{p}$ and $\beta_{AB} < \mathrm{q}$, where p and q are the predefined levels of agreement and disagreement then alternative *A* is declared superior over alternative *B*. If, however, any of these levels of comparison of the alternatives fails, then they are declared to be incomparable.

Core elements at specified levels on a set of non-dominated alternatives are allocated: they have either the relation of incomparability, or the relation of equivalence. If you change the levels of agreement and disagreement from this nucleus so as to strengthen both of them emits then a smaller kernel might be allocated and so on. The latest kernel contains the best alternatives. The sequence of kernels determines the order of alternatives in terms of quality.

Whilst playing around with levels of agreement and disagreement one can get a set of series of possible solutions in the form of various nuclei. However setting weights of the criteria and levels of agreement/disagreement is a very delicate arbitrary issue to be resolved.

Utility Function Based Approaches (MAUT – Multi-Attribute Utility Theory)

These methods are based on the construction of multicriteria utility function (setting relationship between ratings of alternatives based on the criteria and the overall quality of alternatives) and evaluation of each alternative with this function independently of the other alternatives.

When constructing the utility function it must be taken into account that the utility function must satisfy a number of conditions (axioms):

1. Comparability axiom, which states that the ratio can be established between the utility of any alternatives, so that either one of them is superior over the other, or they are equal.
2. Transitivity axiom, which states that if alternative *A* is superiority over alternative *B* and alternative *B* is superior over alternative *C* then alternative *A* should be superior over alternative *B.*
3. Convexity axiom, which states that given an order of relation between the alternatives *A*, *B*, *C*, having form: $U(A) > U(B) > U(C)$, one can find the numbers a and b, which are less than 1 and greater than 0, so that $aU(A)+(1-a)U(C)=U(B), U(A)(1-b)+bU(B)>U(B)$. This axiom is based on the assumption that the utility function is continuous and that it is possible to use any of the small utility alternatives.
4. Independence axiom , which suggest that any of the relationships between the assessments of alternatives on criteria do not depend on the values of other criteria:
    a) Difference independence. Preferences between two alternatives that differ are only estimates based on an ordinal scale of one criterion C_s ad do not depend on the same (fixed) estimates for other criteria $C_1,...,C_{s-1}, C_{s+1},\ldots,C_N$.
    b) Preference independence, which is one of the most important and commonly used terms. It states that two criteria C_1 and C_2 (without loss of generality) are independent

of preference of other criteria $C_3,\ldots,C_N$, if preferences between alternatives , differing only estimates for C_1 and C_2 do not depend on the fixed values of other criteria.

The following utility functions satisfying the axioms above might be addressed:

Arithmetic utility function:

$$F_a = \sum_{i=1}^{N} w_i \frac{z_i}{d_i}; \tag{6.1.55}$$

Geometric utility function:

$$F_g = \prod_{i=1}^{N} \frac{z_i}{d_i}; \tag{6.1.56}$$

Harmonic utility function:

$$F_h = \frac{1}{\sum_{i=1}^{N} \frac{d_i}{w_i \cdot z_i}}; \tag{6.1.57}$$

Exponential utility function:

$$F_p = \sum_{i=1}^{N} (w_i \frac{z_i}{d_i})^p, \tag{6.1.58}$$

where d_i is the scale length of i-th criterion is, w_i is the weight of i-th criterion and z_i is the value of i-th criterion.

There are two major drawbacks of MAUT approach: first, the assumption that people can make accurate quantitative measurements; second, from the DMP it is required to make "immediate" destination all the major parameters without giving him the opportunity to conduct research problems familiar to humans by "trial and error".

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

The TOPSIS method was initially presented by Yoon and Hwang and Lai, Liu, and Hwang (Zopounidis and Doumpos 2002). This method is a process of finding the best solution among all practical alternatives.

In TOPSIS method a positive ideal solution maximizes the benefit criteria or attributes and minimizes the cost criteria or attributes, whereas a negative ideal solution maximizes the cost criteria or attributes and minimizes the benefit criteria or attributes. The TOPSIS method is expressed in a succession of six steps, which are as shown below. Say there are *m* alternatives to be ranked basing on *n* criteria.

- **Step 1: Calculate** the normalized decision matrix (calculate a dimensionless matrix, where x_{ij} is the value of *i*-th alternative on *j*-th criterion). The normalized value r_{ij} is calculated as follows:

$$r_{ij} = x_{ij}\left(\sum_{k=1}^{m} x_{kj}^2\right)^{-\frac{1}{2}}, i = \overline{1,m}, j = \overline{1,n}; \qquad (6.1.59)$$

- **Step 2: Calculate** the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as follows:

$$v_{ij} = r_{ij} \times w_j, i = \overline{1,m}, j = \overline{1,n}; \qquad (6.1.60)$$

where w_j is the weight of the *j*-th criterion or attribute and $\sum_{j=1}^{n} w_j = 1$.

- **Step 3: Determine** the ideal positive A^* and ideal negative A^- solutions.

$$A^* = \{(\max_i v_{ij} \mid j \in C_b), (\min_i v_{ij} \mid j \in C_c)\} = \{v_j^* \mid j = 1, 2, ..., m\}; \qquad (6.1.61)$$

$$A^- = \{(\min_i v_{ij} \mid j \in C_b), (\max_i v_{ij} \mid j \in C_c)\} = \{v_j^- \mid j = 1, 2, ..., m\}; \qquad (6.1.62)$$

- **Step 4: Calculate** the separation measures using the *m*-dimensional Euclidean distance. The separation measures of each alternative from the positive ideal solution and the negative ideal solution, respectively, are as follows:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2}, i = 1, 2, ..., m; \qquad (6.1.63)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, i = 1, 2, ..., m; \qquad (6.1.64)$$

- **Step 5: Calculate** the relative closeness to the ideal solution. The relative closeness of the alternative A_i with respect to A^* is defined as follows:

$$RC_i^* = \frac{S_i^*}{S_i^* + S_i^-}, i = 1, 2, ..., m; \qquad (6.1.65)$$

$$0 \le RC_i^* \le 1. \qquad (6.1.66)$$

- **Step 6: Rank** in the preferred order, so that the smaller the value of RC_i^* the better the corresponding alternative.

The assumption that people can make accurate quantitative measurements of w_j is the major drawback of this method. However as one can see this method has less drawbacks in comparison to both of the methods above. Listing A-21 C# code has been implemented in order to solve TOPSIS problem. This program uses format of Table 21 as input from TOPSIS_INPUT.csv and produces the output in the form of the Table 22, written to TOPSIS_OUTPUT.csv.

In order to slightly smooth the influence of subjective choice of w_j we suggest a two phased usage of TOPSIS, which corresponds to the following algorithm:

❖ **Phase 1:**

- **Select** a set of arbitrary chosen vectors of weights for a given set of criteria forming a matrix: $W = \{w_{i,j}\}, i \in \overline{1,n}, j \in \overline{1,k}$, where *n* is the power of set of criteria and *k* is the power of set of different vectors of weights for a given set of criteria;
- **Estimate** alternatives *k* times with respect to the corresponding vectors of weights of criteria by means of TOPSIS algorithm;

Save RC values of all criteria for each run of TOPSIS: $SRC = \{RC_{i,j}\}, i \in \overline{1,m}, j \in \overline{1,k}$;

❖ **Phase 2:**

- **Set** a vector of equal weights for *k* criteria $\Omega = \{\omega_j = \frac{1}{k}\}, j = \overline{1,k}$. **Let** all of them be loss making, meaning that the smaller the value of the criterion the better;
- **Use** $RC_{i,j}$ as values of criteria *j* for alternative *i*, $i \in \overline{1,m}, j \in \overline{1,k}$ and **rank** the alternative by means of TOPSIS algorithm;
- **Set** ranking from the second phase as final ranking of the set of alternatives.

N	M										
11	6										
Weights											
Value	0.275	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.275
Sign	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Alternatives	LCI{SS}	UCI{Ta}	UCI{Ts}	UCI{Td}	UCI{Da}	UCI{Ds}	UCI{Dd}	UCI{Bfc}	UCI{Ifc}	UCI{Sfc}	UCI{Tfc}
Schedule1	0.95	5	5	5	7	7	7	100	200	300	600
Schedule2	0.99	6	3	6	8	9	7	110	250	340	700
Schedule3	0.91	4	4	6	5	6	7	140	160	300	600
Schedule4	0.8	2	2	5	5	7	9	150	250	250	650
Schedule5	0.95	5	5	5	7	7	7	100	100	350	550
Schedule6	0.99	1	1	1	2	2	2	50	50	50	150

Table 21. *TOPSIS multicriteria ranking input file example*

Alternative	RC value
Schedule6	0
Schedule5	0.694523
Schedule3	0.757824
Schedule1	0.766994
Schedule4	0.781499
Schedule2	0.818565

Table 22. *TOPSIS multicriteria ranking example*

6.2 Estimations of schedules' parameters

In the experiments below the set of vessels with their parameters (Name, ID, Dead Weight, Capacity, Speed(in knots), Fuel Consumption Costs, Fuel Consumption at the base, Fuel Consumption at the installations, Fuel consumption during sailing) represented in Table 23 has been used.

#										
3										
#Vessel	Id	Dead Weight	Capacity	Speed	MinSpeed	MaxSpeed	FCCosts(kr/tonn)	FCSailing(tonn/h)	FCBase(tonn/h)	FCInstallation(tonn/h)
TBN1	0	4847	1000	12	6	20	5000	0.43	0.08	0.26
TBN2	1	4847	1000	12	6	20	5000	0.43	0.08	0.26
TBN3	2	4847	1000	12	6	20	5000	0.43	0.08	0.26

Table 23. *Parameters of the vessels involved into the simulation*

Vessels above are serving the set of installations and the supply base situated at the Norwegian continental shelf nearby Stavanger, which are shown in Table 23. Such parameters as geographical locations, ID, lay times open and closing hours are used as input parameters for these installations, shown in Table 25.

			Summer					
#Start_Hour	Finish_Hour	Weather_	Clusters	Horizon	ReplicationsNum	ClusterCr	Dt	Improvements
2209	6576	3	3;2;2	15	270	1	0.1	0
			Winter					
#Start_Hour	Finish_Hour	Weather_	Clusters	Horizon	ReplicationsNum	ClusterCr	Dt	Improvements
-2184	2208	3	3;2;2	15	270	1	0.1	0

Table 24. *Parameters of the simulation*

#	Size						
12	7						
Node	Id	LatDeg	LonDeg	LayTime	Open	Close	Cranes
FBS	0	59	5.66025	8	8	16	3
DRA	1	58.18833	2.475	2.25	7	19	1
GDR	2	58.83147	1.724972	2.9	0	24	1
GLI	3	58.7	1.666667	4	7	19	1
GRA	4	59.16433	2.485167	3	0	24	1
HDA	5	59.57333	2.228333	4.5	7	19	1
OFP	6	59.05108	5.244122	0	0	24	0
OVA	7	58.569	1.702861	2.9	0	24	1
SLE	8	58.36667	1.911667	4.9	7	19	1
TRL	9	58.63014	1.737639	2.9	0	24	1
VOL	10	58.45	1.9	3.5	0	24	1
WEP	11	58.36944	1.911111	3.3	0	24	1

Table 25. *Parameters of the installations, supply base and an offshore point*

The first schedule to be estimated was a schedule servicing FBS, WEP, SLE, DRA, VOL, GLI by the vessel TBN 3 with the schedule parameters represented in Table B-1 (note that Offshore Point is used as an artificial leg, so as to lead the vessel into the open sea not through the great cycle in order not to cross the mountains and/or land which are situated at the great cycles connecting FBS and any of the installations). This schedule is based on instance 5304-B, with basic (B) strategy for speed optimization incorporated. Such parameters as schedules arrival, discharge and departure times as well as vessels with their id and leg speed are used to define a single weekly schedule within our problem (see the exact definition and its extensions in section 2.1).

We will address two seasons (winter and summer seasons), so that winter season starts on 275th day of the year and ends on the 92nd day of the following year, whilst summer season begins on the 93rd day of the year and ends on the 274th day of the year. These dates have been chosen for practical reasons so as to have equal deviations from the beginning of a year till the dates of changing of the seasons. 10 replications are carried out for each week of these periods. Note that any other length of the time period to be addressed might be set via input parameters of the corresponding input files.

The estimates for key robustness, utilization and cost-related parameters (mathematical expectations, standard deviations, margins of error and confidence intervals of service levels, tardiness, deviations, fuel consumption and fuel cost) for schedule 1 are represented in Table 26 below.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.94354067	0.005048647	0.00021645	0.94332422	0.94375712	0.964912281	0.004119552	0.000180773	0.964731507	0.965093054
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.599396732	0.026974752	0.002910426	0.596486306	0.602307158	0.608371237	0.027502131	0.003037156	0.605334081	0.611408394
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.690909091	0.044061292	0.008234116	0.682674975	0.699143206	0.828571429	0.036780017	0.00703515	0.821536279	0.835606578
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.66969697	0.025890383	0.002793429	0.666903541	0.672490398	0.793650794	0.022801365	0.002518034	0.791132759	0.796168828
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
16.12249198	3.401387892	0.635646837	15.48684515	16.75813882	6.602532587	1.903360978	0.364068063	6.238464524	6.96660065
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
28.59117856	2.987339081	0.558269947	28.03290861	29.1494485	22.34438212	1.602835745	0.306584674	22.03779745	22.6509668
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
14.29621369	12.38088423	14.01028941	0.285924274	28.3065031	9.215015628	7.915642948	8.95739323	0.257622398	18.17240886
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
18.45244255	14.07378465	15.92598658	2.526455968	34.37842912	14.46229881	10.68892471	12.09565697	2.366641836	26.55795578
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
9.777683433	8.784862848	4.775505842	5.00217759	14.55318927	6.859242467	5.854733957	3.182669633	3.676572834	10.0419121
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
14.14270397	14.21637715	7.728110652	6.414593316	21.87081462	12.17943103	12.30866531	6.691066681	5.488364345	18.87049771
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
9.766666169	8.722275829	4.741483152	5.025183017	14.50814932	6.596425137	5.523063618	3.002371583	3.594053553	9.59879672
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
13.11888737	13.22656697	7.19004371	5.928843662	20.30893108	10.6634753	11.27155054	6.127284671	4.536190633	16.79075997
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
10.13570342	8.984839145	4.884214196	5.251489227	15.01991762	6.737274715	5.480770816	2.979380954	3.757893761	9.716655669
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
14.71159771	14.62950125	7.952687467	6.758910241	22.66428518	12.26903899	12.5824298	6.839886754	5.429152238	19.10892575
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
337.3751413	29.01132234	5.421597261	331.9535441	342.7967386	317.0138868	27.92718675	5.341812143	311.6720746	322.3556989
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
20.55953515	1.702936679	0.318242537	20.24129261	20.87777769	20.76690372	1.762512268	0.337127027	20.42977669	21.10403074
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
127.6701109	10.94779018	2.045908441	125.6242024	129.7160193	118.3020529	10.49772541	2.007967275	116.2940856	120.3100202
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
485.6047874	41.62202603	7.778268762	477.8265186	493.3830561	456.0828434	40.17360674	7.684263447	448.3985799	463.7671068
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
2428023.937	208110.1301	38891.34381	2389132.593	2466915.281	2280414.217	200868.0337	38421.31723	2241992.9	2318835.534

Table 26. *Estimates of key parameters of schedule 1 for both winter and summer seasons*

So, in the Table above one can see that those key parameters, connected to service level and average deviations and/or tardiness are significantly better during summer period, which might be explained by better weather conditions (weaker winds and thus lower significant wave heights). Fuel consumptions as well become slightly lower in summer period for the same reasons. Relative comparison of robustness of this schedule to the others will be carried out in the ongoing sections of this thesis.

The 2nd schedule (instance 5304-S) to be estimated is the schedule defined in Table B-2. This schedule is characterized by the key parameters represented in Table 27. One might notice that for this schedule all of the key values have better values in summer in terms of robustness versus fuel consumption, though the difference is not dramatic.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.857894737	0.007312311	0.000300153	0.857594583	0.85819489	0.931578947	0.005287341	0.000217033	0.931361914	0.93179598
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.538216565	0.026275226	0.002714259	0.535502306	0.540930824	0.581463965	0.026000194	0.002685848	0.578778117	0.584149813
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.308333333	0.042156839	0.007542816	0.300790518	0.315876149	0.466666667	0.045542003	0.008148498	0.458518168	0.474815165
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.361111111	0.025315228	0.00261509	0.358496021	0.363726201	0.555555556	0.02618914	0.002705366	0.552850189	0.558260922
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
31.61685293	3.976799478	0.711539708	30.90531323	32.32839264	16.34081473	2.773527454	0.496247026	15.8445677	16.83706176
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
31.61685561	3.976799297	0.711539676	30.90531594	32.32839529	16.34081473	2.773527454	0.496247026	15.8445677	16.83706176
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
24.70503231	21.39518558	24.21093167	0.494100646	48.91596398	11.5993331	10.04531713	11.36734643	0.231986662	22.96667953
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
27.13940878	23.50341744	26.5966206	0.542788176	53.73602937	15.52687704	13.44666996	15.2163395	0.310537541	30.74321653
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
17.10558446	15.87473899	8.629606416	8.475978047	25.73519088	7.814836138	7.855188192	4.270128943	3.544707195	12.08496508
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
20.46461293	17.96685568	9.766894003	10.69771893	30.23150694	12.32382954	11.30232811	6.14401555	6.179813987	18.46784509
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
18.06273	16.31540482	8.869155089	9.193574908	26.93188509	8.204511402	7.859314623	4.272372096	3.932139306	12.4768835
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
20.5885279	17.6993584	9.621480829	10.96704708	30.21000873	11.6069038	10.51077314	5.713721367	5.893182433	17.32062517
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
18.195964	16.59502585	9.021158815	9.174805188	27.21712282	8.114177981	8.047195957	4.374505553	3.739672428	12.48868353
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
21.80137154	18.423539	10.01514988	11.78622165	31.81652142	12.8527545	11.46113669	6.230344877	6.622409624	19.08309938
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
255.0656478	21.01376162	3.759839011	251.3058088	258.8254868	227.7510048	18.72712156	3.350707193	224.4002976	231.101712
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
17.44022508	1.380599569	0.247020605	17.19320447	17.68724568	16.63015766	1.314938823	0.235272407	16.39488526	16.86543007
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
145.3793793	11.96325693	2.140498257	143.2388811	147.5198776	118.5844724	9.78226808	1.750269838	116.8342026	120.3347423
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
417.8852522	34.32754871	6.141977772	411.7432744	424.0272299	362.9656349	29.81174596	5.333998142	357.6316367	368.299633
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
2089426.261	171637.7436	30709.88886	2058716.372	2120136.15	1814828.174	149058.7298	26669.99071	1788158.184	1841498.165

Table 27. *Estimates of key parameters of schedule 2 for both winter and summer seasons*

The 3^{rd} schedule (instance 5304-W) to be estimated is shown in Table B-3, whilst the corresponding key factors are gathered in Table 28. The common trend of significantly better performance during summer season is supported by the results of robustness versus fuel consumption estimation of schedule 3.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.949282297	0.004799592	0.000205772	0.949076524	0.949488069	0.97593985	0.003430751	0.000150548	0.975789302	0.976090397
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.579504672	0.027173907	0.002931914	0.576572758	0.582436586	0.602658075	0.027571628	0.003044831	0.599613244	0.605702906
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.254545455	0.041533345	0.007761696	0.246783758	0.262307151	0.447619048	0.048526501	0.009281975	0.438337073	0.456901023
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.436363636	0.027300262	0.002945547	0.43341809	0.439309183	0.644444444	0.026970637	0.002978462	0.641465983	0.647422906
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
22.01481196	3.187453072	0.595666983	21.41914498	22.61047895	15.64338322	3.429612024	0.65600389	14.98737933	16.29938711
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
22.01481197	3.187453071	0.595666983	21.41914499	22.61047896	15.64338322	3.429612024	0.65600389	14.98737933	16.29938711
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
16.92666759	14.24263821	16.11706237	0.809605225	33.04372996	9.638378545	7.647380566	8.653825768	0.984552778	18.29220431
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
16.92666784	14.24263842	16.11706261	0.80960523	33.04373045	9.638378545	7.647380566	8.653825768	0.984552778	18.29220431
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
11.90147741	10.47537745	5.694480051	6.206997355	17.59595746	6.178994222	6.038468118	3.282548661	2.896445561	9.461542883
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
11.90147769	10.4753777	5.694480187	6.206997503	17.59595788	6.178994222	6.038468118	3.282548661	2.896445561	9.461542883
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
11.81185469	10.49497454	5.705133145	6.106721547	17.51698784	6.021015687	6.093093099	3.312243139	2.708772548	9.333258826
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
11.81186107	10.49497845	5.705135272	6.106725798	17.51699634	6.021025416	6.093096719	3.312245107	2.708780309	9.333270522
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
11.54578338	9.844788176	5.351687814	6.194095565	16.89747119	5.748935973	5.387142714	2.928484138	2.820451835	8.677420111
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
12.49072291	10.84696003	5.896474637	6.594248272	18.38719755	7.052316451	8.224988022	4.471154421	2.581162031	11.52347087
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
296.0035106	25.551294	4.774991775	291.2285188	300.7785024	277.5814238	24.51544411	4.689226245	272.8921976	282.27065
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
16.82209169	1.391809825	0.260099565	16.56199212	17.08219126	18.12349605	1.540007936	0.294567196	17.82892885	18.41806324
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
121.847148	10.52295832	1.96651643	119.8806315	123.8136644	103.1677393	9.092271676	1.739137124	101.4286021	104.9068764
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
434.6727503	37.45016011	6.998636019	427.6741142	441.6713863	398.8726591	35.13857958	6.721181505	392.1514776	405.5938406
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
2173363.751	187250.8006	34993.18009	2138370.571	2208356.931	1994363.296	175692.8979	33605.90752	1960757.388	2027969.203

Table 28. *Estimates of key parameters of schedule 3 for both winter and summer seasons*

The 4th schedule (5304-R) to be estimated is depicted in Table B-4, whilst its estimates are shown in Table 29.

The 5th schedule (10304-B) to be analyzed is shown in Table B-5. Note that this schedule has a greater demand for servicing of the installations and two vessels are used to do that. As one can see in Table 30 this schedule already has a way lower service level and much greater tardiness and/or deviations, where tardiness creates a greater part of deviations (which means that the vessels are late in most of the occasions), moreover difference between summer and winter seasons is much more significant for this schedule, which means it is less robust to weather changes in comparison to the previous ones, though it is still a rather competitive in terms of robustness schedule. More poor results of schedule 5 in comparison to first 4 schedules can also be explained by the fact that size of the problem for building this schedule is relatively large and thus finding an optimal or close to optimal solution in terms of the key parameters we estimate might become a rather more sophisticated task.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.884688995	0.006986466	0.00029953	0.884389465	0.884988525	0.913283208	0.006300614	0.000276482	0.913006726	0.91355969
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.571790494	0.027238905	0.002938927	0.568851567	0.57472942	0.587418391	0.02773789	0.003063192	0.584355199	0.590481583
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.372727273	0.046102815	0.008615633	0.36411164	0.381342905	0.542857143	0.048615426	0.009298984	0.533558158	0.552156127
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.409090909	0.027065327	0.002920199	0.406170711	0.412011108	0.565079365	0.027932156	0.003084645	0.56199472	0.56816401
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
25.70303379	3.323923959	0.62117048	25.08186331	26.32420427	22.74937546	4.347606707	0.831594622	21.91778084	23.58097008
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
25.70303379	3.323923959	0.62117048	25.08186331	26.32420427	22.74937546	4.347606707	0.831594622	21.91778084	23.58097008
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
19.09542931	16.25703665	18.3965688	0.698860515	37.49199811	15.04062272	13.02556137	14.73981027	0.300812454	29.78043299
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
21.76245901	18.56613008	21.00955399	0.752905017	42.772013	18.61252487	16.11891937	18.24027437	0.372250497	36.85279924
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
13.51381802	11.91337288	6.47618327	7.037634746	19.99000129	11.39256209	10.16700372	5.526846177	5.865715911	16.91940827
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
17.12846605	14.33971168	7.795156063	9.333309983	24.92362211	16.02663789	13.80064574	7.502116484	8.524521408	23.52875438
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
14.13487765	12.36668249	6.722605181	7.412272467	20.85748283	11.77524959	10.52043244	5.718972219	6.056277372	17.49422181
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
16.82816105	14.03946825	7.631941875	9.19621918	24.46010293	15.22796967	13.18940385	7.169841603	8.058128067	22.39781127
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
13.84716707	12.40759303	6.744844402	7.102322669	20.59201147	12.07174962	10.84683628	5.896407371	6.175342253	17.968157
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
17.71524457	14.52871786	7.897900994	9.817343579	25.61314557	16.96540188	14.26088065	7.752303029	9.21309885	24.71770491
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
256.9756845	22.18652612	4.146188438	252.8294961	261.121873	240.6802451	21.21941894	4.058774369	236.6214708	244.7390195
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
16.37562953	1.342347318	0.250856078	16.12477345	16.62648561	15.6680151	1.313956399	0.251328869	15.41668623	15.91934397
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
128.6911085	11.11439854	2.077043989	126.6140645	130.7681525	124.2792019	10.91487506	2.087758164	122.1914438	126.3669601
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
402.0424226	34.62819189	6.471270359	395.5711522	408.5136929	380.6274622	33.42325037	6.393079485	374.2343827	387.0205417
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
2010212.113	173140.9595	32356.35179	1977855.761	2042568.465	1903137.311	167116.2519	31965.39743	1871171.914	1935102.708

Table 29. *Estimates of key parameters of schedule 4 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.881349206	0.00455506	0.000125758	0.881223449	0.881474964	0.908730159	0.004056634	0.000111997	0.908618162	0.908842156
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.612648261	0.019887616	0.001591341	0.61105692	0.614239602	0.631383208	0.019695112	0.001575937	0.629807271	0.632959145
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.333333333	0.043033148	0.007699607	0.325633726	0.341032941	0.458333333	0.045484786	0.008138261	0.450195073	0.466471594
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.476666667	0.020390176	0.001631554	0.475035113	0.478298221	0.575	0.020181468	0.001614854	0.573385146	0.576614854
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
31.59970411	3.913231571	0.700165967	30.89953814	32.29987007	30.27289035	3.890445522	0.696089025	29.57680132	30.96897938
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
31.59970411	3.913231571	0.700165967	30.89953814	32.29987007	30.27289035	3.890445522	0.696089025	29.57680132	30.96897938
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
25.16542754	14.06790166	12.33105949	12.83436804	37.49648703	20.65470526	11.54633126	10.12080558	10.53389968	30.77551084
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
25.16542754	14.06790166	12.33105949	12.83436804	37.49648703	20.65470526	11.54633126	10.12080558	10.53389968	30.77551084
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
16.29231787	9.985284438	3.459724546	12.83259332	19.75204241	12.77224877	8.19053303	2.837874909	9.934373865	15.61012368
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
16.29253457	9.985397438	3.459763698	12.83277087	19.75229827	12.77224877	8.19053303	2.837874909	9.934373865	15.61012368
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
16.52551761	9.996182836	3.463500648	13.06201696	19.98901826	12.86485791	8.1046847	2.80812998	10.05672793	15.67298789
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
16.52573431	9.996247393	3.463523016	13.0622113	19.98925733	12.86485791	8.1046847	2.80812998	10.05672793	15.67298789
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
17.68252548	10.11617468	3.505075701	14.17744978	21.18760118	13.59887174	7.848739835	2.719449609	10.87942213	16.31832135
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
18.11066898	10.33310926	3.580239698	14.53042928	21.69090868	14.09272108	8.317220779	2.881769975	11.21095111	16.97449105
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1259.609039	110.171908	19.71225547	1239.896784	1279.321295	1238.975586	108.3493789	19.38616365	1219.589423	1258.36175
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
81.08586041	6.916861785	1.237583601	79.84827681	82.32344401	94.10479077	8.065702366	1.443137262	92.66165351	95.54792804
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
805.7852364	70.47141107	12.60893529	793.1763011	818.3941716	719.6777201	63.054237	11.28183446	708.3958856	730.9595546
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2146.480136	187.5327584	33.55386787	2112.926268	2180.034004	2052.758097	179.4499455	32.10766914	2020.650428	2084.865767
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
10732400.68	937663.792	167769.3393	10564631.34	10900170.02	10263790.49	897249.7275	160538.3457	10103252.14	10424328.83

Table 30. *Estimates of key parameters of schedule 5 for both winter and summer seasons*

In order to provide a more compact output characteristics of the instances for schedules 6-12 (that might be found in Tables B-6 – B-12 in the appendix) as well as for the other schedules, the correspondences between schedules, instances they are based upon and speed optimization strategies incorporated are represented in Table 31, whilst the estimates of key parameters of schedules 6-12 are shown in Tables 32-38.

Schedule	Instance	Strategy
Schedule1	5304	B
Schedule2	5304	S
Schedule3	5304	W
Schedule4	5304	R
Schedule5	10304	B
Schedule6	10304	R
Schedule7	10344	B
Schedule8	10304	W
Schedule9	10344	W
Schedule10	10344	R
Schedule11	10344	S
Schedule12	10304	S

Table 31. *Correspondence between schedules, instances and strategies*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.825974026	0.005577881	0.000160844	0.825813182	0.82613487	0.894104308	0.004633551	0.000136757	0.893967551	0.894241066
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.584790684	0.021011276	0.001756011	0.583034673	0.586546695	0.666583056	0.02057507	0.001760021	0.664823035	0.668343076
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0.00952381	0.00947835	0.001812985	0.007710825	0.011336794
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.341818182	0.02022503	0.0016903	0.340127881	0.343508482	0.495238095	0.021820799	0.001866582	0.493371513	0.497104677
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
18.29809831	3.888543325	0.726685795	17.57141251	19.0247841	10.00123445	2.969924041	0.568076421	9.433158034	10.56931088
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
18.29809831	3.888543325	0.726685795	17.57141251	19.0247841	10.00123445	2.969924041	0.568076421	9.433158034	10.56931088
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
33.6770114	18.82602169	16.50173559	17.17527581	50.17874699	20.64523265	11.54103591	10.116164	10.52906865	30.76139665
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
33.6770114	18.82602169	16.50173559	17.17527581	50.17874699	20.64523265	11.54103591	10.116164	10.52906865	30.76139665
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
23.75786694	11.68970371	4.050275696	19.70759124	27.80814264	13.37404682	7.450959808	2.581625861	10.79242096	15.95567268
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
23.75786694	11.68970371	4.050275696	19.70759124	27.80814264	13.37404682	7.450959808	2.581625861	10.79242096	15.95567268
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
24.11609255	11.98611932	4.152978464	19.96311408	28.26907101	13.48193348	7.548143383	2.615298252	10.86663523	16.09723173
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
24.11609255	11.98611932	4.152978464	19.96311408	28.26907101	13.48193348	7.548143383	2.615298252	10.86663523	16.09723173
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
25.22211385	12.12576715	4.201363967	21.02074988	29.42347781	13.78736386	7.369323505	2.553340325	11.23402354	16.34070419
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
25.56023809	12.19578792	4.225624928	21.33461316	29.78586301	14.25073055	7.827439532	2.712069431	11.53866112	16.96279998
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
955.749961	87.1965535	16.29517573	939.4547853	972.0451368	878.4169137	82.07379047	15.69878035	862.7181333	894.115694
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
66.60607945	5.94424959	1.110853443	65.49522601	67.71693289	74.33380196	6.816280125	1.303793621	73.03000834	75.63759558
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
804.7245675	73.68022238	13.76926178	790.9553057	818.4938292	658.2845653	61.90047468	11.84010084	646.4444644	670.1246661
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1827.080608	166.8006292	31.17147932	1795.909129	1858.252087	1611.035281	150.7818261	28.84100704	1582.194274	1639.876288
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9135403.04	834003.146	155857.3966	8979545.643	9291260.436	8055176.405	753909.1306	144205.0352	7910971.369	8199381.44

Table 32. *Estimates of key parameters of schedule 6 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.893650794	0.00434246	0.000119888	0.893530905	0.893770682	0.927777778	0.003646214	0.000100666	0.927677112	0.927878444
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.644587748	0.019540317	0.001563551	0.643024197	0.646151299	0.653246891	0.019430019	0.001554725	0.651692166	0.654801617
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.466666667	0.045542003	0.008148498	0.458518168	0.474815165	0.558333333	0.045331853	0.008110898	0.550222436	0.566444231
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.555	0.020288544	0.001623422	0.553376578	0.556623422	0.695	0.018796055	0.001503998	0.693496002	0.696503998
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
32.96363814	4.259982974	0.762207665	32.20143047	33.7258458	19.28024121	3.041642579	0.544218909	18.7360223	19.82446012
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
32.96363814	4.259982974	0.762207665	32.20143047	33.7258458	19.28024121	3.041642579	0.544218909	18.7360223	19.82446012
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
25.84197435	14.44610283	12.66256743	13.17940692	38.50454178	13.99383208	7.82278995	6.85697772	7.136854361	20.8508098
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
25.84197435	14.44610283	12.66256743	13.17940692	38.50454178	13.99383208	7.82278995	6.85697772	7.136854361	20.8508098
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
16.99820968	9.711041572	3.36470424	13.63350543	20.36291392	9.205682135	5.174083439	1.792728448	7.412953687	10.99841058
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
16.9982121	9.711041363	3.364704168	13.63350794	20.36291627	9.205682135	5.174083439	1.792728448	7.412953687	10.99841058
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
16.9114779	9.438346845	3.270220338	13.64125757	20.18169824	9.06222155	4.973356531	1.723180123	7.339041427	10.78540167
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
16.91148081	9.438346459	3.270220204	13.64126061	20.18170101	9.062222237	4.973356845	1.723180232	7.339042005	10.78540247
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
17.88143877	9.226045626	3.196661719	14.68477705	21.07810049	9.9086406	5.001056937	1.732777824	8.175862776	11.64141842
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
18.38909026	9.748757734	3.377772224	15.01131804	21.76686248	10.48165396	5.594303959	1.93832743	8.543326534	12.41998139
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1320.993683	115.6780469	20.69742873	1300.296255	1341.691112	1226.62493	107.2666055	19.1924309	1207.432499	1245.817361
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
78.38370231	6.657485349	1.191175268	77.19252704	79.57487758	85.72256206	7.301081688	1.306329264	84.4162328	87.02889133
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
791.3445723	69.52889081	12.44029702	778.9042753	803.7848693	643.7339625	56.26573655	10.06721762	633.6667448	653.8011801
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2190.721958	191.8461794	34.32563681	2156.396321	2225.047595	1956.081454	170.7979994	30.55963957	1925.521815	1986.641094
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
10953609.79	959230.8972	171628.1841	10781981.61	11125237.97	9780407.272	853989.997	152798.1978	9627609.074	9933205.47

Table 33. *Estimates of key parameters of schedule 7 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.791341991	0.005978313	0.000172391	0.791169601	0.791514382	0.837868481	0.00555012	0.00016381	0.837704671	0.83803229
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.539389459	0.021253811	0.00177628	0.537613178	0.541165739	0.564831368	0.021637573	0.001850909	0.56298046	0.566682277
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0	0	0	0	0
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.28	0.019145377	0.001600069	0.278399931	0.281600069	0.32952381	0.02051424	0.001754817	0.327768992	0.331278627
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
0	0	0	0	0	0	0	0	0	0
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
0	0	0	0	0	0	0	0	0	0
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
41.21927087	23.04227291	20.19744273	21.02182814	61.4167136	31.69375847	17.7173496	15.52994165	16.16381682	47.22370011
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
43.72295244	24.44187346	21.42424669	22.29870574	65.14719913	34.50995015	19.29164861	16.90987557	17.60007458	51.41982572
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
31.79268232	18.57838908	6.437083404	25.35559891	38.22976572	23.23778694	16.24597039	5.628941556	17.60884539	28.8667285
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
35.16188284	19.55406452	6.775137693	28.38674515	41.93702053	27.03553579	16.93584012	5.867969223	21.16756657	32.90350502
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
31.72855947	18.12294434	6.279279852	25.44927962	38.00783932	23.16382495	15.7420339	5.454336469	17.70948848	28.61816142
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
34.70308986	19.12247972	6.625601189	28.07748867	41.32869105	26.51123582	16.58058155	5.744878409	20.76635741	32.25611423
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
32.32267165	18.09832184	6.270748589	26.05192306	38.59342024	23.61020387	15.68322354	5.43395972	18.17624415	29.04416359
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
35.85167026	19.33040621	6.697644044	29.15402622	42.54931431	27.62650939	16.82879113	5.830878641	21.79563075	33.45738803
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1018.681493	93.12131056	17.40238643	1001.279106	1036.083879	976.5796289	91.320523	17.46746219	959.1121668	994.0470911
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
66.22834261	5.899790349	1.102544959	65.12579765	67.33088757	68.46896586	6.24516478	1.194552726	67.27441313	69.66351858
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
752.1135784	68.94140544	12.88367798	739.2299004	764.9972564	696.5184086	65.38885138	12.50734503	684.0110636	709.0257537
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1837.023414	167.9522486	31.38669243	1805.636721	1868.410106	1741.567003	162.947801	31.16807109	1710.398932	1772.735075
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9185117.068	839761.2432	156933.4621	9028183.606	9342050.53	8707835.017	814739.005	155840.3555	8551994.662	8863675.373

Table 34. *Estimates of key parameters of schedule 8 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.902046784	0.004295827	0.000121682	0.901925102	0.902168465	0.951963241	0.003090437	8.75E-05	0.951875703	0.95205078
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.558543403	0.020798645	0.001707472	0.556835931	0.560250875	0.601437941	0.020507181	0.001683545	0.599754396	0.603121485
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.447368421	0.046569126	0.008548733	0.438819688	0.455917154	0.614035088	0.04559509	0.008369928	0.60566516	0.622405016
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.563157895	0.020774946	0.001705527	0.561452368	0.564863422	0.687719298	0.01941068	0.001593527	0.686125771	0.689312825
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
36.34192421	5.371633915	0.986075237	35.35584897	37.32799945	21.14950499	4.343034855	0.797254466	20.35225052	21.94675945
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
45.38007201	4.896849861	0.89891874	44.48115327	46.27899075	33.18202368	3.904304657	0.716716404	32.46530728	33.89874009
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
25.86822876	14.46077949	12.67543209	13.19279667	38.54366085	14.99373992	6.937752704	6.08120837	8.912531549	21.07494829
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
28.47730236	15.49967882	13.58606751	14.89123486	42.06336987	18.22465487	8.240523607	7.223137414	11.00151746	25.44779229
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
20.87791158	13.37777543	4.635162703	16.24274888	25.51307428	11.59486418	7.551021145	2.616295346	8.978568837	14.21115953
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
24.32990604	16.62050888	5.758712523	18.57119352	30.08861857	15.68486973	11.77813933	4.080917074	11.60395265	19.7657868
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
20.86373705	13.21710642	4.579493734	16.28424332	25.44323079	11.41230837	7.437660714	2.57701796	8.835290406	13.98932633
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
23.8948975	15.98317818	5.537888701	18.3570088	29.4327862	14.99242108	10.99193064	3.80850966	11.18391142	18.80093074
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
22.06015612	13.31726714	4.614197652	17.44595847	26.67435377	11.87679513	7.453999981	2.582679228	9.2941159	14.45947436
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
25.6711029	16.08317289	5.5725351	20.0985678	31.243638	16.08987387	11.23437869	3.892513623	12.19736024	19.98238749
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1312.451746	118.7253953	21.79451807	1290.657228	1334.246264	1239.082243	112.0806937	20.57474475	1218.507499	1259.656988
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
83.34436688	7.339718306	1.347358101	81.99700878	84.69172498	86.15660082	7.580998087	1.391650028	84.7649508	87.54825085
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
780.1511735	70.24229358	12.89443537	767.2567381	793.0456088	612.9229548	55.22524732	10.13774388	602.7852109	623.0606987
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2175.947286	196.2825449	36.03174753	2139.915539	2211.979034	1938.161799	174.8766069	32.10224196	1906.059557	1970.264041
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
10879736.43	981412.7244	180158.7377	10699577.69	11059895.17	9690808.994	874383.0343	160511.2098	9530297.785	9851320.204

Table 35. *Estimates of key parameters of schedule 9 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.89390142	0.004450641	0.000126067	0.893775353	0.894027487	0.921261487	0.003892315	1.10E-04	0.921151235	0.921371739
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.545817452	0.020854583	0.001712065	0.544105387	0.547529516	0.587134387	0.020622233	0.00169299	0.585441397	0.588827377
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.473684211	0.046764385	0.008584576	0.465099634	0.482268787	0.49122807	0.046822083	0.008595168	0.482632902	0.499823238
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.415789474	0.020643532	0.001694738	0.414094735	0.417484212	0.49122807	0.020939472	0.001719034	0.489509037	0.492947104
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
36.93269124	4.918475232	0.902888527	36.02980271	37.83557977	35.69674598	4.835423685	0.887642686	34.8091033	36.58438867
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
38.00364129	4.862522684	0.892617272	37.11102401	38.89625856	36.38673111	4.800003856	0.881140639	35.50559047	37.26787175
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
33.51694528	18.73654201	16.42330319	17.09364209	49.94024847	26.31263715	13.63745178	11.95375354	14.35888361	38.26639068
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
33.73113529	18.85627787	16.52825629	17.202879	50.25939158	26.45063417	13.66220002	11.97544633	14.47518785	38.4260805
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
24.89089374	14.00074632	4.851011105	20.03988264	29.74190485	18.94229402	11.63637315	4.031797596	14.91049643	22.97409162
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
25.36445763	14.55473196	5.042957338	20.32150029	30.40741497	19.40982802	12.1737631	4.217993717	15.19183431	23.62782174
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
25.13120468	13.86489822	4.803942139	20.32726254	29.93514682	19.02896059	11.45207975	3.967943193	15.0610174	22.99690378
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
25.61630213	14.43881003	5.002792439	20.61350969	30.61909457	19.50451008	12.01732281	4.163789921	15.34072016	23.6683
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
26.06493728	13.94115892	4.830365125	21.23457216	30.89530241	19.50199842	11.37121667	3.939925564	15.56207285	23.44192398
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
26.90441432	14.66916532	5.082606473	21.82180785	31.98702079	20.39311279	12.09825623	4.191831922	16.20128087	24.58494471
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1057.491364	95.39172629	17.51113733	1039.980227	1075.002502	1028.099826	92.7342897	17.02330952	1011.076516	1045.123135
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
66.96406842	5.850659665	1.074010387	65.89005804	68.03807881	66.12821	5.768479244	1.05892446	65.06928554	67.18713446
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
799.3850446	72.02842684	13.22231731	786.1627273	812.6073619	705.8632715	63.63040702	11.68068593	694.1825856	717.5439575
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1923.840477	173.2546844	31.80450433	1892.035973	1955.644982	1800.091307	162.1164105	29.75984226	1770.331465	1829.85115
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9619202.387	866273.4221	159022.5216	9460179.865	9778224.908	9000456.537	810582.0525	148799.2113	8851657.326	9149255.749

Table 36. *Estimates of key parameters of schedule 10 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.865800866	0.005014907	0.00014461	0.865656256	0.865945476	0.925396825	0.003956611	1.17E-04	0.925280048	0.925513603
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.536915032	0.021261886	0.001776955	0.535138077	0.538691987	0.605613714	0.021329423	0.001824549	0.603789165	0.607438263
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.418181818	0.04703053	0.008789003	0.409392815	0.426970821	0.542857143	0.048615426	0.009298984	0.533558158	0.552156127
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.423636364	0.021069953	0.001760915	0.421875449	0.425397278	0.580952381	0.021533881	0.001842039	0.579110342	0.58279442
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
31.11778389	4.591362445	0.858027696	30.25975619	31.97581158	25.31352559	3.783755397	0.723743165	24.58978243	26.03726876
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
31.11778389	4.591362445	0.858027696	30.25975619	31.97581158	25.31352559	3.783755397	0.723743165	24.58978243	26.03726876
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
30.79742304	17.21628286	15.09073729	15.70668575	45.88816033	19.86228165	11.10335299	9.732518007	10.12976364	29.59479966
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
32.46297245	18.14735329	15.9068565	16.55611595	48.36982895	22.1797372	12.39885003	10.86807123	11.31166597	33.04780843
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
25.44663418	12.39375984	4.294218696	21.15241548	29.74085288	14.42664162	7.380089951	2.557070709	11.86957091	16.98371233
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
28.05254701	14.52319492	5.03203031	23.0205167	33.08457732	18.0154182	10.67740738	3.69953291	14.31588529	21.71495111
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
25.6456789	12.40902143	4.299506568	21.34617233	29.94518547	14.41380013	7.41006689	2.567457188	11.84634294	16.98125732
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
27.95253223	14.48179028	5.017684334	22.9348479	32.97021656	17.5861137	10.54663028	3.654220958	13.93189274	21.24033466
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
27.17286687	12.80063378	4.435193324	22.73767355	31.60806019	14.90528385	7.510992606	2.602426165	12.30285768	17.50771001
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
29.85948687	14.91066612	5.166282233	24.69320464	35.02576911	18.59456616	10.6487683	3.689609975	14.90495618	22.28417613
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1032.361998	94.64651088	17.68741384	1014.674585	1050.049412	972.1426402	91.26805738	17.45742676	954.6852134	989.600067
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
63.9960819	5.682671369	1.061970053	62.93411185	65.05805196	68.58904607	6.233296232	1.192282553	67.39676352	69.78132863
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
832.5424665	76.10736152	14.22284231	818.3196242	846.7653088	657.6609257	61.72595282	11.80671892	645.8542068	669.4676446
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1928.900547	176.4035586	32.96606198	1895.934485	1961.866609	1698.392612	159.2130139	30.4536944	1667.938918	1728.846306
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9644502.734	882017.7931	164830.3099	9479672.424	9809333.044	8491963.06	796065.0693	152268.472	8339694.588	8644231.532

Table 37. *Estimates of key parameters of schedule 11 for both winter and summer seasons*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.875108225	0.004863812	0.000140253	0.874967972	0.875248478	0.900680272	0.004503849	1.33E-04	0.900547343	0.900813201
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.617924918	0.020718622	0.001731552	0.616193366	0.61965647	0.641749051	0.020926502	0.001790083	0.639958968	0.643539134
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.263636364	0.042009981	0.007850769	0.255785594	0.271487133	0.40952381	0.047989489	0.009179257	0.400344552	0.418703067
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.394545455	0.020840491	0.001741737	0.392803717	0.396287192	0.506666667	0.021819849	0.001866501	0.504800166	0.508533167
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
34.03895851	4.022204251	0.751664171	33.28729434	34.79062268	30.15149695	4.453376029	0.851825798	29.29967115	31.00332275
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
34.03895851	4.022204251	0.751664171	33.28729434	34.79062268	30.15149695	4.453376029	0.851825798	29.29967115	31.00332275
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
26.597496	14.86845227	13.03277304	13.56472296	39.63026903	21.62590546	12.08924867	10.59669368	11.02921179	32.22259914
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
26.597496	14.86845227	13.03277304	13.56472296	39.63026903	21.62590546	12.08924867	10.59669368	11.02921179	32.22259914
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
18.30505358	9.646808865	3.342448743	14.96260484	21.64750232	14.49872846	8.243929903	2.856375982	11.64235248	17.35510444
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
18.30505358	9.646808865	3.342448743	14.96260484	21.64750232	14.49872846	8.243929903	2.856375982	11.64235248	17.35510444
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
18.42202991	9.576001554	3.317915261	15.10411465	21.73994517	14.66019802	8.319869433	2.882687686	11.77751034	17.54288571
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
18.42202991	9.576001554	3.317915261	15.10411465	21.73994517	14.66019802	8.319869433	2.882687686	11.77751034	17.54288571
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
18.98167372	9.421607202	3.264420348	15.71725337	22.24609406	15.01165199	8.151072731	2.824202613	12.18744938	17.8358546
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
19.38541684	9.634769508	3.338277319	16.04713953	22.72369416	15.4657368	8.224989537	2.84981348	12.61592332	18.31555028
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
931.9392143	85.18588071	15.91942388	916.0197904	947.8586382	878.1577168	82.14438077	15.71228261	862.4454342	893.8699994
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
68.61758003	6.124521756	1.144542465	67.47303756	69.76212249	72.73335644	6.653678212	1.27269171	71.46066473	74.00604815
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
718.1462034	65.93425004	12.32170479	705.8244987	730.4679082	674.6122829	63.45978989	12.13836106	662.4739219	686.750644
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1718.702998	157.234385	29.38375235	1689.319245	1748.08675	1625.503356	152.2471593	29.12129072	1596.382065	1654.624647
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
8593514.989	786171.9249	146918.7617	8446596.227	8740433.751	8127516.781	761235.7967	145606.4536	7981910.327	8273123.235

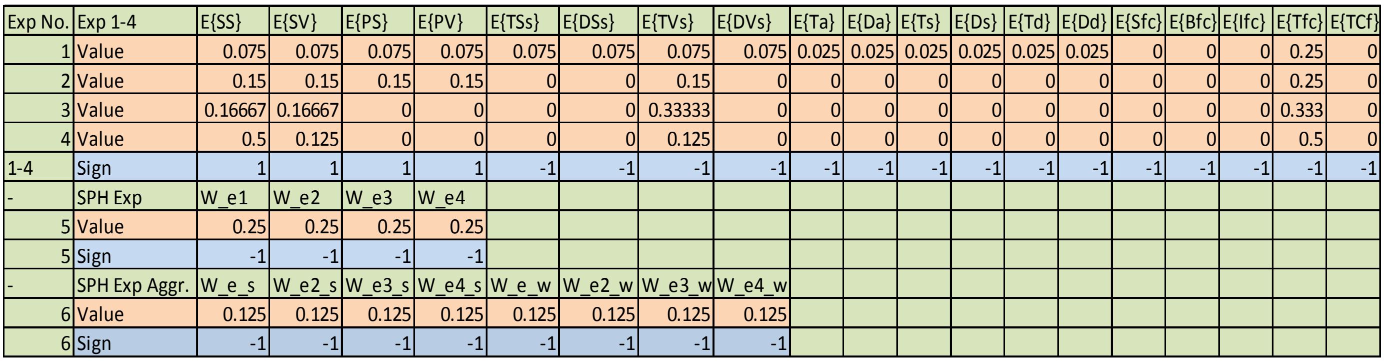
Table 38. *Estimates of key parameters of schedule 12 for both winter and summer seasons*

With respect to everything mentioned above, all schedules except for schedules 6 and 8 may be claimed as relatively robust, though a slight difference between summer and winter seasons is present. Schedules 6 and 8 are much less robust and have a relatively low level of all service level related parameters. A more detailed and fair multicriteria ranking has to be carried out in order to give just and fair objective estimated of the schedules. This comparison of robustness versus fuel consumption for the given set of schedules is provided in the ongoing section 6.3.

6.3 *TOPSIS Multicriteria ranking of schedules*

Two phases of TOPSIS method are used for ranking of schedules (alternatives) with the following set of criteria for the first phase: A1={ E{SS}, E{SV}, E{PS}, E{PV}, E{TSs}, E{DSs}, E{TVs}, E{DVs}, E{Ta}, E{Da}, E{Ts}, E{Ds}, E{Td}, E{Dd}, E{Sfc}, E{Bfc}, E{Ifc}, E{Tfc}, E{TCf}}, which have the corresponding weighs represented in Table 39, these weights are used in order put stress on the most important for the company factors from the perspective of several managers (4 in our case). Afterwards the second phase of multicriteria ranking is run with the same set of alternatives, but the set of criteria represented by RC-values of the first phase results of multicriteria ranking: A2(a) = {W_e1, W_e2, W_e3, W_e4} or A2(b) = {W_e1_s, W_e2_s, W_e3_s, W_e4_s, W_e1_w, W_e2_w, W_e3_w, W_e4_w }, so that A2(a) does not aggregated the seasonal results, whilst A2(b) does this.

Note that only schedules based on the same instances might be compared between one another with respect to all of the robustness parameters above.



Exp No.	Exp 1-4	E{SS}	E{SV}	E{PS}	E{PV}	E{TSs}	E{DSs}	E{TVs}	E{DVs}	E{Ta}	E{Da}	E{Ts}	E{Ds}	E{Td}	E{Dd}	E{Sfc}	E{Bfc}	E{Ifc}	E{Tfc}	E{TCf}
1	Value	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.025	0.025	0.025	0.025	0.025	0.025	0	0	0	0.25	0
2	Value	0.15	0.15	0.15	0.15	0	0	0.15	0	0	0	0	0	0	0	0	0	0	0.25	0
3	Value	0.16667	0.16667	0	0	0	0	0.33333	0	0	0	0	0	0	0	0	0	0	0.333	0
4	Value	0.5	0.125	0	0	0	0	0.125	0	0	0	0	0	0	0	0	0	0	0.5	0
1-4	Sign	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-	SPH Exp	W_e1	W_e2	W_e3	W_e4															
5	Value	0.25	0.25	0.25	0.25															
5	Sign	-1	-1	-1	-1															
-	SPH Exp Aggr.	W_e_s	W_e2_s	W_e3_s	W_e4_s	W_e_w	W_e2_w	W_e3_w	W_e4_w											
6	Value	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125											
6	Sign	-1	-1	-1	-1	-1	-1	-1	-1											

Table 39. *Criteria and their weights for the 2 phased TOPSIS algorithm*

Thus, we have a set of schedules represented in Table 40 to be ranked with respect to the criteria shown in Table 39. The results of these 2 phased TOPSIS rankings for instances consisting of 5 and 10 installations are represented in Tables 41 and 42 correspondingly.

Alternatives	E{SS}	E{SV}	E{PS}	E{PV}	E{TSs}	E{DSs}	E{TVs}	E{DVs	E{Ta}	E{Da}	E{Ts}	E{Ds}	E{Td}	E{Dd}	E{Sfc}	E{Bfc}	E{Ifc}	E{Tfc}	E{TCf}
Schedule1-W-5304-B	0.944	0.599	0.691	0.67	16.12	28.59	14.3	18.45	9.778	14.14	9.767	13.12	10.14	14.71	337.4	20.56	127.7	485.6	2E+06
Schedule1-S-5304-B	0.965	0.608	0.829	0.794	6.603	22.34	9.215	14.46	6.859	12.18	6.596	10.66	6.737	12.27	317	20.77	118.3	456.1	2E+06
Schedule2-W-5304-S	0.858	0.538	0.308	0.361	31.62	31.62	24.71	27.14	17.11	20.46	18.06	20.59	18.2	21.8	255.1	17.44	145.4	417.9	2E+06
Schedule2-S-5304-S	0.932	0.581	0.467	0.556	16.34	16.34	11.6	15.53	7.815	12.32	8.205	11.61	8.114	12.85	227.8	16.63	118.6	363	2E+06
Schedule3-W-5304-W	0.949	0.58	0.255	0.436	22.01	22.01	16.93	16.93	11.9	11.9	11.81	11.81	11.55	12.49	296	16.82	121.8	434.7	2E+06
Schedule3-S-5304-W	0.976	0.603	0.448	0.644	15.64	15.64	9.638	9.638	6.179	6.179	6.021	6.021	5.749	7.052	277.6	18.12	103.2	398.9	2E+06
Schedule4-W-5304-R	0.885	0.572	0.373	0.409	25.7	25.7	19.1	21.76	13.51	17.13	14.13	16.83	13.85	17.72	257	16.38	128.7	402	2E+06
Schedule4-S-5304-R	0.913	0.587	0.543	0.565	22.75	22.75	15.04	18.61	11.39	16.03	11.78	15.23	12.07	16.97	240.7	15.67	124.3	380.6	2E+06
Schedule5-W-10304-B	0.881	0.613	0.333	0.477	31.6	31.6	25.17	25.17	16.29	16.29	16.53	16.53	17.68	18.11	1260	81.09	805.8	2146	1E+07
Schedule5-S-10304-B	0.909	0.631	0.458	0.575	30.27	30.27	20.65	20.65	12.77	12.77	12.86	12.86	13.6	14.09	1239	94.1	719.7	2053	1E+07
Schedule6-W-10304-R	0.826	0.585	0	0.342	18.3	18.3	33.68	33.68	23.76	23.76	24.12	24.12	25.22	25.56	955.7	66.61	804.7	1827	9E+06
Schedule6-S-10304-R	0.894	0.667	0.01	0.495	10	10	20.65	20.65	13.37	13.37	13.48	13.48	13.79	14.25	878.4	74.33	658.3	1611	8E+06
Schedule7-W-10344-B	0.894	0.645	0.467	0.555	32.96	32.96	25.84	25.84	17	17	16.91	16.91	17.88	18.39	1321	78.38	791.3	2191	1E+07
Schedule7-S-10344-B	0.928	0.653	0.558	0.695	19.28	19.28	13.99	13.99	9.206	9.206	9.062	9.062	9.909	10.48	1227	85.72	643.7	1956	1E+07
Schedule8-W-10304-W	0.791	0.539	0	0.28	0	0	41.22	43.72	31.79	35.16	31.73	34.7	32.32	35.85	1019	66.23	752.1	1837	9E+06
Schedule8-S-10304-W	0.838	0.565	0	0.33	0	0	31.69	34.51	23.24	27.04	23.16	26.51	23.61	27.63	976.6	68.47	696.5	1742	9E+06
Schedule9-W-10344-W	0.902	0.559	0.447	0.563	36.34	45.38	25.87	28.48	20.88	24.33	20.86	23.89	22.06	25.67	1312	83.34	780.2	2176	1E+07
Schedule9-S-10344-W	0.952	0.601	0.614	0.688	21.15	33.18	14.99	18.22	11.59	15.68	11.41	14.99	11.88	16.09	1239	86.16	612.9	1938	1E+07
Schedule10-W-10344-R	0.894	0.546	0.474	0.416	36.93	38	33.52	33.73	24.89	25.36	25.13	25.62	26.06	26.9	1057	66.96	799.4	1924	1E+07
Schedule10-S-10344-R	0.921	0.587	0.491	0.491	35.7	36.39	26.31	26.45	18.94	19.41	19.03	19.5	19.5	20.39	1028	66.13	705.9	1800	9E+06
Schedule11-W-10344-S	0.866	0.537	0.418	0.424	31.12	31.12	30.8	32.46	25.45	28.05	25.65	27.95	27.17	29.86	1032	64	832.5	1929	1E+07
Schedule11-S-10344-S	0.925	0.606	0.543	0.581	25.31	25.31	19.86	22.18	14.43	18.02	14.41	17.59	14.91	18.59	972.1	68.59	657.7	1698	8E+06
Schedule12-W-10304-S	0.875	0.618	0.264	0.395	34.04	34.04	26.6	26.6	18.31	18.31	18.42	18.42	18.98	19.39	931.9	68.62	718.1	1719	9E+06

Table 40. *Winter and summer combined multicriteria ranking input parameters for schedules 1-12*

Schedule	Exp 1	Exp 2	Exp 3	Exp 4	SPH Exp
Schedule3-S-5304-W	0.307244	0.397087	0.084206	0.210287	0.163673
Schedule2-S-5304-S	0.351295	0.428244	0.14916	0.113117	0.179851
Schedule1-S-5304-B	0.271679	0.181715	0.184181	0.458295	0.263711
Schedule4-S-5304-R	0.474817	0.438948	0.360031	0.265863	0.35235
Schedule1-W-5304-B	0.475896	0.360584	0.396696	0.637661	0.48963
Schedule3-W-5304-W	0.602473	0.712129	0.50357	0.538752	0.650358
Schedule4-W-5304-R	0.661497	0.701222	0.608426	0.463011	0.700317
Schedule2-W-5304-S	0.819982	0.848386	0.859813	0.639203	1

Table 41(a). *Winter and summer separate multicriteria ranking for schedules 1-4*

Alternative	Aggr. RC value
Schedule3-5304-W	0.338837382
Schedule1-5304-B	0.439379567
Schedule2-5304-S	0.475623179
Schedule4-5304-R	0.662099366

Table 41(b). *Winter and summer aggregated multicriteria ranking for schedules 1-4*

In Tables 41(a) and 42(a) one can see that all of the schedules perform significantly better in summer, so that almost always the worst performance of the set of schedules in summer outranks the best performance on the same set of schedules in winter, meaning that the worst schedule in summer performs slightly better than the best one in winter (the only exception is by far the worst schedule 8 in Table 42). The most robust and simultaneously cheap schedule with respect to 2 phased TOPSIS algorithm (Table 41(b)) is schedule 3 on the subset of schedules 1-4, based on the instances of size 5, whilst the worst schedule in terms of robustness versus fuel consumption approach is schedules 4 that performs badly both in summer and in winter; schedule 1 is performing very stably in terms of RC-values which are on one hand good enough but on the other hand do not dramatically differ in summer and winter seasons; schedule 2 in turn performs significantly worse in winter than any of the other schedules and has the biggest difference in terms of RC-values between its performance in summer and in winter, though its aggregated measure is still better than those of schedule 4.

Schedule	Exp 1	Exp 2	Exp 3	Exp 4	SPH Exp
Schedule11-S-10344-S	0.377033	0.180951	0.214209	0.186731	0.093162
Schedule7-S-10344-B	0.30115	0.147717	0.150334	0.380493	0.170898
Schedule9-S-10344-W	0.379588	0.133717	0.156461	0.372537	0.175035
Schedule12-S-10304-S	0.450309	0.326329	0.264955	0.179006	0.217414
Schedule6-S-10304-R	0.413189	0.600152	0.230626	0.159553	0.353877
Schedule5-S-10304-B	0.474794	0.301282	0.305717	0.525219	0.36515
Schedule10-S-10344-R	0.53255	0.330514	0.442424	0.376183	0.388924
Schedule12-W-10304-S	0.582515	0.540952	0.441022	0.324521	0.483059
Schedule7-W-10344-B	0.548	0.366304	0.479887	0.669751	0.527983
Schedule9-W-10344-W	0.618406	0.381224	0.484451	0.672566	0.54762
Schedule5-W-10304-B	0.579601	0.48475	0.455815	0.651075	0.570882
Schedule11-W-10344-S	0.602545	0.467748	0.613983	0.580483	0.620894
Schedule10-W-10344-R	0.626067	0.451194	0.698804	0.60069	0.65337
Schedule8-S-10304-W	0.475108	0.77021	0.61092	0.433687	0.689401
Schedule6-W-10304-R	0.611412	0.803571	0.685978	0.527573	0.810562
Schedule8-W-10304-W	0.538092	0.86761	0.847248	0.61657	0.918058

Table 42(a). *Winter and summer separate multicritea ranking for schedules 5-12*

Alternative	Aggr. RC value
Schedule11-10344-S	0.216614321
Schedule7-10344-B	0.262778096
Schedule12-10304-S	0.263248859
Schedule9-10344-W	0.269293833
Schedule5-10304-B	0.446757827
Schedule6-10304-R	0.476054772
Schedule10-10344-R	0.495494269
Schedule8-10304-W	0.882344811

Table 42(b). *Winter and summer aggregated multicritea ranking for schedules 5-12*

Tables 42(a) and 42(b) in general supports the ideas described in the previous paragraph: schedules 7, 9, 11 and 12 might be considered as the best in terms of robustness versus fuel consumption with schedule 11 over performing all others, whilst schedule 8 being by far the worst one. Other schedules are somewhere in between. From Tables 41(a, b) and 42(a, b) it seems to be a rather difficult task to say which of the speed optimization strategies (B, W, R or S) is the best one in a statistically significant way (the sample is relatively small, moreover all schedules have dynamic nature behind them and might well be highly dependent upon the instances they are based on), however it might be noticed that the worst one might be considered R-strategy, which is almost always outperformed by other strategies on the same types of instances behind them.

In the ongoing sections of our research we will provide the technics to carry out a posteriori improvements of schedules and estimate their efficiency based on comparison with the estimates represented in sections 6.2 and 6.3.

6.4 A Posteriori improvements and corresponding estimates

Schedules 7 (as one of the best in terms of robustness versus fuel consumption), 8 (as by far the worst in terms of robustness versus fuel consumption), 10 and 12 (as those somewhere in between) have been chosen for a posteriori improvements and further evaluation. Note that this set of schedules covers all four speed optimization strategies and thus we can formally compare them for possibility of a posteriori improvements (though in a statistically insignificant way, since the sample is very small and no one can prove it to be very representative, moreover the given sample is not random at all).

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.802597403	0.005856044	0.000168865	0.802428538	0.802766268	0.947619048	0.003138256	8.66E-05	0.947532405	0.94770569
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.554920637	0.021191067	0.001771037	0.5531496	0.556691673	0.690630689	0.018870609	0.001509963	0.689120725	0.692140652
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0.658333333	0.043294587	0.007746385	0.650586949	0.666079718
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.314545455	0.019799293	0.00165472	0.312890735	0.316200174	0.768333333	0.01722388	0.001378197	0.766955136	0.769711531
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
0	0	0	0	0	14.28560115	2.581911192	0.461962527	13.82363862	14.74756368
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
0	0	0	0	0	15.79067544	2.527365975	0.452203149	15.33847229	16.24287859
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
36.52276464	20.41684612	17.89615468	18.62660997	54.41891932	11.46722066	6.410371228	5.618938124	5.848282537	17.08615878
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
39.3926152	22.02114135	19.30238145	20.09023375	58.69499665	13.10496254	7.325896768	6.421431642	6.683530893	19.52639418
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
28.82066355	17.65916159	6.118587325	22.70207623	34.93925088	6.989620048	4.76209868	1.649983012	5.339637036	8.63960306
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
32.15355707	18.55507857	6.429006723	25.72455035	38.5825638	8.436130385	6.00943944	2.082164536	6.353965849	10.51829492
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
28.79409896	17.49550306	6.06188254	22.73221642	34.8559815	6.97450247	4.786513256	1.658442231	5.316060239	8.632944702
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
32.23192915	18.54792542	6.426528283	25.80540087	38.65845743	8.93689475	6.259066418	2.168655871	6.768238879	11.10555062
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
29.38736573	17.60712173	6.100556433	23.2868093	35.48792216	7.577923787	4.994418775	1.730477818	5.847445969	9.308401606
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
33.54632476	18.95885213	6.568907123	26.97741764	40.11523188	10.14140698	7.135596352	2.472357999	7.669048983	12.61376498
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1034.180097	94.53809061	17.6671524	1016.512944	1051.847249	1214.897245	106.3385382	19.02637859	1195.870866	1233.923623
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
63.27846257	5.647114907	1.055325309	62.22313726	64.33378788	69.58573951	5.939925394	1.062787502	68.52295201	70.64852702
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
709.2258319	64.84813898	12.1187338	697.1070981	721.3445657	603.8613697	52.73160902	9.434881974	594.4264877	613.2962517
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1806.684391	165.0200871	30.83873398	1775.845657	1837.523125	1888.344354	164.9873338	29.51997958	1858.824374	1917.864334
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9033421.957	825100.4354	154193.6699	8879228.287	9187615.627	9441721.77	824936.669	147599.8979	9294121.872	9589321.668

Table 43. *Estimates of key parameters of schedule 8 in winter (left column) and schedule 7 in summer (right column) after improvement of type 1*

Tables 43 and 44 claim that improvement of type one leads to a slight reduction of both tardiness and fuel cost of the schedules, however does not always significantly improve the service level. Which might be explained by the fact that whilst departing from the supply base before the planned time (which is moreover hardly ever possible in practice) vessels' voyages do not match the working hours of the installations at some point and the advantage achieved gets relatively soon dispersed during the time of sailing.

		Winter						Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%		E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.885338346	0.004604544	0.000130426	0.885207919	0.885468772		0.900680272	0.004503849	1.33E-04	0.900547343	0.900813201
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%		E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.554645916	0.020817243	0.001708999	0.552936917	0.556354915		0.651592648	0.020794673	0.001778806	0.649813843	0.653371454
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%		E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.543859649	0.046648775	0.008563354	0.535296295	0.552423003		0.419047619	0.048151221	0.009210193	0.409837426	0.428257812
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%		E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.489473684	0.020938054	0.001718917	0.487754767	0.491192601		0.504761905	0.021820799	0.001866582	0.502895323	0.506628487
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%		E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
32.95060449	5.465681286	1.00333959	31.9472649	33.95394408		31.92027996	4.040024198	0.772761342	31.14751862	32.6930413
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%		E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
33.5851396	5.440706326	0.998754917	32.58638468	34.58389452		31.92027996	4.040024198	0.772761342	31.14751862	32.6930413
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%		E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
34.81738382	19.46350925	17.06051807	17.75686575	51.87790189		21.22152171	7.05791745	6.186537414	15.03498429	27.40805912
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%		E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
34.94429084	19.53445244	17.12270251	17.82158833	52.06699335		21.26823455	7.081382511	6.207105446	15.0611291	27.47534
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%		E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
26.43364195	14.63636409	5.071241425	21.36240053	31.50488338		13.50229734	9.240265924	3.201588801	10.30070854	16.70388614
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%		E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
26.88842616	15.04522807	5.212905567	21.6755206	32.10133173		13.56668622	9.244602749	3.203091434	10.36359478	16.76977765
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%		E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
26.68922314	14.64327979	5.073637596	21.61558555	31.76286074		13.5433933	9.192678644	3.185100649	10.35829265	16.72849395
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%		E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
27.19855179	15.10663885	5.234183319	21.96436848	32.43273511		13.60817514	9.18268109	3.181636673	10.42653847	16.78981181
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%		E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
27.96335491	14.59534941	5.057030566	22.90632434	33.02038548		13.81680636	8.973255741	3.109074492	10.70773187	16.92588086
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%		E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
28.87177658	15.03911936	5.210789008	23.66098757	34.08256559		14.34554273	9.337091229	3.235137057	11.11040567	17.58067979
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%		E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1035.526301	93.38750344	17.1432205	1018.383081	1052.669522		892.4196316	83.51217101	15.97390862	876.4457229	908.3935402
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%		E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
64.69381671	5.652997996	1.037725472	63.65609124	65.73154218		72.08987934	6.60083825	1.262584672	70.82729467	73.35246401
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%		E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
858.9467291	77.47266706	14.22172095	844.7250082	873.1684501		651.4952341	61.23565951	11.71293738	639.7822967	663.2081715
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%		E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1959.166847	176.4849133	32.39748009	1926.769367	1991.564327		1616.004745	151.3423403	28.94822019	1587.056525	1644.952965
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%		E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9795834.236	882424.5666	161987.4005	9633846.836	9957821.637		8080023.725	756711.7016	144741.1009	7935282.624	8224764.826

Table 44. *Estimates of key parameters of schedules 10 in winter (left column) and schedule 12 in summer (right column) after improvement of type 1*

		Winter						Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%		E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.82987013	0.005528081	0.000159408	0.829710722	0.830029538		0.959325397	0.002782463	7.68E-05	0.959248578	0.959402216
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%		E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.56345911	0.02114766	0.001767409	0.561691701	0.565226519		0.680019015	0.01904351	0.001523798	0.678495217	0.681542814
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%		E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0		0.716666667	0.041135503	0.007360075	0.709306591	0.724026742
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%		E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.472727273	0.021288332	0.001779166	0.470948107	0.474506438		0.823333333	0.015570033	0.001245862	0.822087471	0.824579195
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%		E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
0	0	0	0	0		15.72049263	2.897324697	0.518397164	15.20209547	16.2388898
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%		E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
0	0	0	0	0		15.72049263	2.897324697	0.518397164	15.20209547	16.2388898
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%		E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
34.40989742	19.23571743	16.86084974	17.54904769	51.27074716		10.86078009	6.025803534	5.281849678	5.578930408	16.14262976
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%		E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
36.71351768	20.52348031	17.98962366	18.72389402	54.70314134		10.86093592	6.025890637	5.281926027	5.579009891	16.14286194
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%		E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
24.89727039	14.34832689	4.97144163	19.92582876	29.86871202		6.64457622	4.324521812	1.498370362	5.146205858	8.142946583
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%		E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
27.93862065	16.55244461	5.735129456	22.20349119	33.67375011		6.666449121	4.3168263	1.495704003	5.170745118	8.162153125
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%		E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
24.84994375	14.15069234	4.902964751	19.946979	29.75290851		6.414104615	4.058404347	1.406165365	5.00793925	7.82026998
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%		E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
27.50031741	16.11585439	5.583858662	21.91645875	33.08417607		6.432669466	4.053007386	1.404295413	5.028374053	7.836964879
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%		E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
25.81513381	14.47623171	5.015758386	20.79937542	30.83089219		6.967329026	4.181416804	1.448787007	5.518542019	8.416116033
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%		E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
29.00165371	16.71181025	5.790346834	23.21130688	34.79200055		7.611747184	5.297429958	1.835465837	5.776281347	9.447213021
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%		E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1473.380147	135.1822103	25.26267132	1448.117476	1498.642819		1401.993581	122.700868	21.95397085	1380.03961	1423.947552
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%		E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
68.81979752	6.133722615	1.146261909	67.67353561	69.96605943		93.34189011	7.966850234	1.425450371	91.91643974	94.76734049
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%		E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
791.177243	72.48662267	13.54620346	777.6310395	804.7234465		607.3711835	53.2504022	9.52770585	597.8434776	616.8988893
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%		E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2333.377188	213.7821308	39.95131973	2293.425868	2373.328508		2102.706655	183.9032874	32.9044731	2069.802181	2135.611128
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%		E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
11666885.94	1068910.654	199756.5986	11467129.34	11866642.54		10513533.27	919516.4368	164522.3655	10349010.91	10678055.64

Table 45. *Estimates of key parameters of schedule 8 in winter (left column) and schedule 7 in summer (right column) after improvement of type 2*

As one can see in Tables 45 and 46 improvements of type 2 lead to significant improvement of service level related parameters and even more significant than in case of improvement of type 1 decrease of tardiness-related parameters, on the other hand fuel costs become much higher, since in most of the occasions the leg speed is significantly increased with respect to the weather forecast. We were expecting that the amount of times when the speed is increased and decreased would neutralize each other given better utilized schedules with high service levels, which are simultaneously cheap enough. Unfortunately the last did not work well enough on the chosen instances.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.91374269	0.00405726	0.000114924	0.913627766	0.913857614	0.929251701	0.00386105	1.14E-04	0.929137743	0.929365658
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.57798522	0.020686393	0.001698257	0.576286963	0.579683477	0.658287289	0.020699443	0.00177066	0.65651663	0.660057949
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.657894737	0.044433002	0.008156603	0.649738134	0.666051339	0.476190476	0.048739649	0.009322745	0.466867731	0.485513222
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.640350877	0.020100695	0.001650174	0.638700703	0.642001051	0.565714286	0.021632499	0.001850475	0.563863811	0.56756476
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
26.36138581	4.696080693	0.862063379	25.49932243	27.22344919	24.73240437	4.145897555	0.793012418	23.93939195	25.52541679
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
27.2648803	4.667745391	0.856861845	26.40801846	28.12174215	24.73240437	4.145897555	0.793012418	23.93939195	25.52541679
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
23.82670979	13.3195357	11.6750878	12.151622	35.50179759	16.81364368	9.399112555	8.238685404	8.574958277	25.05232909
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
24.04051436	13.43905608	11.77985204	12.26066233	35.8203664	16.81969516	9.402495436	8.241650629	8.578044533	25.06134579
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
18.65296707	11.47129261	3.974600109	14.67836696	22.62756718	11.04703936	6.873323723	2.381485169	8.665554195	13.42852453
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
19.37412482	12.17594779	4.218750671	15.15537415	23.5928755	11.13747874	6.868384781	2.379773913	8.757704828	13.51725265
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
18.62911381	11.23481894	3.892666164	14.73644764	22.52177997	10.93568476	6.786115469	2.35126905	8.584415713	13.28695381
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
19.34643992	11.98171481	4.151452379	15.19498754	23.4978923	11.01908128	6.778401508	2.348596299	8.670484979	13.36767758
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
19.78229272	11.16999922	3.870207275	15.91208544	23.65249999	11.68338638	6.932116333	2.401855769	9.281530611	14.08524215
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
20.98376754	12.60792007	4.368421432	16.6153461	25.35218897	12.31798162	7.566486046	2.621653661	9.696327954	14.93963528
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1353.632876	122.186019	22.42978758	1331.203088	1376.062663	1114.904662	104.3503807	19.95976665	1094.944896	1134.864429
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
65.10694198	5.678886243	1.042477799	64.06446418	66.14941978	74.62368165	6.851097907	1.310453442	73.31322821	75.93413509
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
773.4146079	69.68196907	12.79157614	760.6230318	786.2061841	666.170167	62.55028997	11.96439518	654.2057719	678.1345622
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2192.154426	197.5247758	36.25978488	2155.894641	2228.414211	1855.698511	173.734998	33.23140745	1822.467104	1888.929918
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
10960772.13	987623.879	181298.9244	10779473.2	11142071.05	9278492.555	868674.9899	166157.0373	9112335.518	9444649.592

Table 46. *Estimates of key parameters of schedules 10 in winter (left column) and schedule 12 in summer (right column) after improvement of type 2*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.852164502	0.005221919	0.000150579	0.852013923	0.852315081	0.964880952	0.002592943	7.16E-05	0.964809365	0.964952539
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.591861968	0.020957159	0.001751488	0.59011048	0.593613456	0.696381772	0.018772063	0.001502078	0.694879694	0.69788385
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0.75	0.039528471	0.007072541	0.742927459	0.757072541
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.496363636	0.021319508	0.001781771	0.494581865	0.498145407	0.83	0.015335145	0.001227067	0.828772933	0.831227067
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
1.011424966	1.016053938	0.189878806	0.82154616	1.201303772	13.75527761	2.595435221	0.464382283	13.29089532	14.21965989
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
1.011424966	1.016053938	0.189878806	0.82154616	1.201303772	13.86706058	2.592841134	0.463918142	13.40314244	14.33097872
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
28.99507868	16.20874173	14.20758855	14.78749012	43.20266723	8.867904467	4.373887462	3.833881399	5.034023068	12.70178587
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
31.56403291	17.64483081	15.46637613	16.09765679	47.03040904	8.890724065	4.38612877	3.844611378	5.046112686	12.73533544
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
20.94046489	11.28430637	3.909812683	17.03065221	24.85027757	5.431538818	3.72182072	1.289545088	4.14199373	6.721083906
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
24.44975353	13.68136322	4.740350506	19.70940303	29.19010404	5.478874968	3.731088884	1.292756343	4.186118625	6.771631311
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
20.75031941	11.02863377	3.821226646	16.92909277	24.57154606	5.261196531	3.408859351	1.181109506	4.080087025	6.442306037
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
23.80426943	13.20533656	4.575415686	19.22885375	28.37968512	5.308290238	3.424225402	1.186433571	4.121856667	6.494723809
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
21.34780451	11.02344964	3.819430437	17.52837408	25.16723495	5.635961195	3.43919922	1.191621734	4.444339461	6.82758293
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
24.94267986	13.49786314	4.676770974	20.26590888	29.61945083	6.304131477	4.807144891	1.665590728	4.638540749	7.969722205
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1514.193032	138.9929848	25.97482379	1488.218209	1540.167856	1467.613202	128.4874896	22.98932882	1444.623873	1490.602531
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
70.50617604	6.280399521	1.173672694	69.33250335	71.67984874	94.96263613	8.097564901	1.448838193	93.51379794	96.41147432
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
760.2554658	69.88449209	13.05992076	747.1955451	773.3153866	592.7551366	52.02276301	9.308053329	583.4470833	602.06319
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2344.954674	215.1483426	40.20663559	2304.748039	2385.16131	2155.330975	188.5979608	33.74445677	2121.586518	2189.075431
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
11724773.37	1075741.713	201033.1779	11523740.19	11925806.55	10776654.87	942989.8042	168722.2838	10607932.59	10945377.16

Table 47. *Estimates of key parameters of schedule 8 in winter (left column) and schedule 7 in summer (right column) after improvement of type 3*

Improvements of type 3 only increase the sailing speed at those legs, where this is necessary to minimize tardiness with regard to the corresponding weather forecasts. One would expect this to increase service level and sailing fuel consumption (as well as total fuel consumption) due to only increases in fuel consumption per time unit, one would also expect even greater in comparison to other improvements decrease of tardiness. All of these ideas find their confirmation in Tables 47 and 48 in comparison to the Tables, describing the estimates of the corresponding schedules without a posteriori improvements.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.94695071	0.003239115	9.17E-05	0.94685896	0.94704246	0.932426304	0.003779869	1.12E-04	0.932314743	0.932537865
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.591722918	0.020587294	0.001690121	0.590032797	0.59341304	0.661024621	0.020659188	0.001767216	0.659257405	0.662791837
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.649122807	0.04469805	0.008205258	0.640917549	0.657328065	0.666666667	0.046004371	0.008799551	0.657867116	0.675466218
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.661403509	0.019821524	0.001627255	0.659776253	0.663030764	0.702857143	0.019945114	0.001706133	0.70115101	0.704563276
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
21.47697288	4.060457499	0.745381509	20.73159137	22.22235439	20.58219949	4.453092035	0.851771477	19.73042802	21.43397097
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
22.19176025	4.042234134	0.742036231	21.44972402	22.93379648	20.58219949	4.453092035	0.851771477	19.73042802	21.43397097
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
17.42018523	9.738179589	8.535890763	8.884294468	25.95607599	14.14196566	7.905599135	6.929563171	7.212402484	21.07152883
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
17.63617791	9.858923165	8.641727174	8.994450732	26.27790508	14.14246617	7.905878934	6.929808425	7.212657749	21.0722746
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
12.81289592	8.027171458	2.781273012	10.03162291	15.59416893	8.888404486	6.390593043	2.214227521	6.674176965	11.10263201
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
13.58412824	8.6759618	3.006067397	10.57806085	16.59019564	8.949389979	6.3773751	2.209647738	6.739742241	11.15903772
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
12.71944661	7.915769384	2.742674163	9.976772452	15.46212078	8.827134683	6.26383847	2.170309303	6.65682538	10.99744399
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
13.48708406	8.597924552	2.97902887	10.50805519	16.46611293	8.884795541	6.251364085	2.165987149	6.718808392	11.05078269
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
13.67898011	8.106758183	2.808848405	10.8701317	16.48782852	9.515985155	6.015959789	2.084423721	7.431561433	11.60040888
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
14.93224673	9.105419244	3.15486681	11.77737992	18.08711354	10.16287606	6.774987593	2.347413438	7.815462625	12.5102895
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1339.484067	120.9271093	22.19868851	1317.285379	1361.682756	1052.566926	98.48124563	18.83713954	1033.729786	1071.404065
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
66.33290621	5.77664082	1.060422687	65.27248352	67.3933289	77.79051299	7.14082143	1.365870718	76.42464227	79.1563837
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
696.3859695	62.64603756	11.49998443	684.885985	707.8859539	623.2889721	58.47571736	11.18502554	612.1039466	634.4739977
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2102.202943	189.3256469	34.75466406	2067.448279	2136.957607	1753.646411	164.0712524	31.38296084	1722.26345	1785.029372
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
10511014.72	946628.2343	173773.3203	10337241.39	10684788.04	8768232.054	820356.2618	156914.8042	8611317.25	8925146.858

Table 48. *Estimates of key parameters of schedules 10 in winter (left column) and schedule 12 in summer (right column) after improvement of type 3*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.813636364	0.005728947	0.0001652	0.813471164	0.813801564	0.926785714	0.003669208	0.000101301	0.926684413	0.926887015
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.528044335	0.021286509	0.001779013	0.526265322	0.529823348	0.672210801	0.019163483	0.001533398	0.670677403	0.673744199
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0.558333333	0.045331853	0.008110898	0.550222436	0.566444231
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.3	0.019540168	0.001633063	0.298366937	0.301633063	0.675	0.019121323	0.001530025	0.673469975	0.676530025
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
0	0	0	0	0	23.30689108	3.57392021	0.639455461	22.66743562	23.94634654
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
0	0	0	0	0	23.30689108	3.57392021	0.639455461	22.66743562	23.94634654
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
33.90884033	18.955618	16.61533176	17.29350857	50.52417209	17.98583521	10.05438754	8.813059252	9.172775956	26.79889446
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
36.0151784	20.13309678	17.64743741	18.36774098	53.66261581	17.98583521	10.05438754	8.813059252	9.172775956	26.79889446
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
26.24024307	15.52248753	5.378267535	20.86197553	31.6185106	10.98051518	6.460870529	2.238577428	8.74193775	13.21909261
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
29.26663688	16.33923457	5.661255947	23.60538093	34.92789283	10.98051518	6.460870529	2.238577428	8.74193775	13.21909261
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
26.18253021	15.25975849	5.287236568	20.89529364	31.46976678	10.88683059	6.290249131	2.17946013	8.707370462	13.06629072
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
28.89431546	16.11835581	5.584725359	23.3095901	34.47904082	10.88683059	6.290249131	2.17946013	8.707370462	13.06629072
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
26.95135851	15.55851656	5.390750957	21.56060755	32.34210947	11.50106491	6.250965331	2.165848988	9.335215919	13.66691389
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
30.27112926	16.66719255	5.774887589	24.49624167	36.04601684	12.04810953	6.812299407	2.360341322	9.687768206	14.40845085
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
958.5955853	87.48190513	16.34850186	942.2470834	974.9440871	1199.148152	104.8566848	18.76124137	1180.386911	1217.909393
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
63.8115394	5.684258691	1.06226669	62.74927271	64.87380609	81.27810375	6.912258711	1.236760006	80.04134374	82.51486376
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
680.892462	62.05562921	11.5968733	669.2955887	692.4893353	682.1093337	59.79106514	10.69797894	671.4113548	692.8073126
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1703.299587	155.2029424	29.00411907	1674.295468	1732.303706	1962.535589	171.5436924	30.69306097	1931.842528	1993.22865
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
8516497.933	776014.7121	145020.5953	8371477.338	8661518.529	9812677.947	857718.4618	153465.3048	9659212.642	9966143.252

Table 49. *Estimates of key parameters of schedule 8 in winter (left column) and schedule 7 in summer (right column) after improvement of type 4*

Improvements of type 4 are focused on reduction of fuel consumption only by means of reducing sailing speed when the vessel is sailing faster in terms of arrival, discharge and departure times than it was scheduled and of course taking into consideration the weather forecasts. One would expect that the service level and tardiness remain the same, whilst the deviations and fuel consumptions significantly decrease. However, as we can see from Tables 49 and 50 the idea of decrease of fuel consumption and the corresponding costs always works, whereas tardiness and deviations (as the results of the increase of tardiness) sometimes also increase, moreover in one outcome out of four service level significantly decreases, this might be explained by not really high precision of the forecasts (the reasons for which are described in the chapter dedicated to statistical data analysis) and thus the forecasts underestimates SHW (for instance) and thus engine speed reductions might become too high, which in turn might lead to the delays and outfitting of time windows at the installations, however as one can see in the corresponding Tables this is not always the case.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.927736007	0.003741934	0.000105992	0.927630014	0.927841999	0.865759637	0.005133587	1.52E-04	0.865608121	0.865911153
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.559537786	0.020793692	0.001707066	0.55783072	0.561244852	0.619786008	0.021186308	0.001812307	0.617973702	0.621598315
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.464912281	0.046713841	0.008575298	0.456336983	0.473487579	0.247619048	0.042122707	0.00805708	0.239561967	0.255676128
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.433333333	0.020755703	0.001703947	0.431629386	0.43503728	0.392380952	0.021310321	0.001822915	0.390558037	0.394203867
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
28.71164592	3.999806223	0.734247704	27.97739821	29.44589362	42.58232375	5.100042343	0.975517812	41.60680594	43.55784156
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
29.61567644	3.958299162	0.726628219	28.88904822	30.34230466	42.58232375	5.100042343	0.975517812	41.60680594	43.55784156
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
25.47597396	14.24150239	12.48322724	12.99274672	37.9592012	29.3129654	16.38644582	14.36335305	14.94961236	43.67631845
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
25.65678007	14.34257608	12.57182223	13.08495783	38.2286023	29.3129654	16.38644582	14.36335305	14.94961236	43.67631845
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
20.04392624	11.48270962	3.978555901	16.06537034	24.02248214	19.89128415	11.79661974	4.087320207	15.80396395	23.97860436
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
20.49291928	12.00918124	4.160969012	16.33195027	24.65388829	19.89128415	11.79661974	4.087320207	15.80396395	23.97860436
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
20.17137793	11.39899041	3.949548674	16.22182925	24.1209266	20.07386714	11.79478479	4.086684429	15.98718271	24.16055157
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
20.63016162	11.94097977	4.137338408	16.49282322	24.76750003	20.07386714	11.79478479	4.086684429	15.98718271	24.16055157
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
20.83396017	11.45246021	3.968075016	16.86588515	24.80203518	20.70323217	11.60458798	4.020784598	16.68244758	24.72401677
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
21.67816396	12.09039515	4.189108196	17.48905577	25.86727216	21.13578193	11.69126057	4.05081512	17.08496681	25.18659705
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
988.5735237	89.1944182	16.3734924	972.2000313	1004.947016	899.6809161	84.15924056	16.09767776	883.5832383	915.7785939
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
64.86034333	5.660652699	1.039130652	63.82121268	65.89947398	70.57719497	6.466188416	1.236829334	69.34036563	71.8140243
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
725.2431679	65.28059098	11.98361156	713.2595563	737.2267795	734.5514931	69.01475086	13.20089408	721.350599	747.7523872
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1778.677035	160.1121711	29.39192239	1749.285113	1808.068957	1704.809604	159.6251361	30.53252367	1674.27708	1735.342128
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
8893385.175	800560.8555	146959.612	8746425.563	9040344.787	8524048.021	798125.6807	152662.6184	8371385.402	8676710.639

Table 50. *Estimates of key parameters of schedules 10 in winter (left column) and schedule 12 in summer (right column) after improvement of type 4*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.856277056	0.005161183	0.000148828	0.856128228	0.856425884	0.952777778	0.002987815	8.25E-05	0.952695289	0.952860266
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.56402372	0.021144566	0.00176715	0.562256569	0.56579087	0.683028186	0.018995644	0.001519968	0.681508218	0.684548154
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0.591666667	0.044869925	0.008028248	0.583638418	0.599694915
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.436363636	0.021146692	0.001767328	0.434596308	0.438130964	0.705	0.018617868	0.00148974	0.70351026	0.70648974
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
0	0	0	0	0	17.76458999	2.55293048	0.45677722	17.30781277	18.22136721
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
0	0	0	0	0	17.76458999	2.55293048	0.45677722	17.30781277	18.22136721
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
33.98265801	18.99688334	16.65150242	17.33115558	50.63416043	11.92156541	6.664357663	5.84156705	6.079998359	17.76313246
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
34.77430671	19.43942842	17.03941029	17.73489642	51.813717	11.92156541	6.664357663	5.84156705	6.079998359	17.76313246
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
26.59640812	15.48510355	5.365314645	21.23109347	31.96172276	6.795913904	4.630672945	1.604446318	5.191467586	8.400360222
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
29.87172408	16.85834342	5.841117987	24.03060609	35.71284207	6.795913904	4.630672945	1.604446318	5.191467586	8.400360222
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
26.36085417	15.41696931	5.341707338	21.01914683	31.70256151	6.64199365	4.551104927	1.576877406	5.065116244	8.218871056
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
29.49604469	16.88485472	5.850303683	23.64574101	35.34634837	6.641994213	4.551104921	1.576877404	5.065116809	8.218871617
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
26.94540139	15.50416905	5.371920504	21.57348089	32.31732189	7.031246004	4.589385062	1.590140796	5.441105208	8.621386801
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
30.64151068	17.13250412	5.936109824	24.70540086	36.57762051	7.628214279	5.361348583	1.85761251	5.770601769	9.485826789
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1029.327289	94.27285738	17.61758597	1011.709703	1046.944875	1246.901087	109.0503583	19.51158478	1227.389503	1266.412672
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
65.32588233	5.834720898	1.090384867	64.23549746	66.41626719	84.31679542	7.174304421	1.283645933	83.03314949	85.60044135
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
707.6194418	64.88085854	12.12484839	695.4945934	719.7442902	597.5941444	52.28516328	9.355002695	588.2391417	606.9491471
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1802.272613	164.9759181	30.83047974	1771.442133	1833.103092	1928.812027	168.4951283	30.14760365	1898.664424	1958.959631
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9011363.063	824879.5903	154152.3987	8857210.665	9165515.462	9644060.136	842475.6414	150738.0182	9493322.118	9794798.154

Table 51. *Estimates of key parameters of schedule 8 in winter (left column) and schedule 7 in summer (right column) after improvement of type 5*

Like improvements of first type improvements of type five are expected to reduce the waiting times at the supply base by means of reassigning the remaining vessel schedules between the identical vessels if one of them is currently delayed, whilst some other one arrives before the scheduled time. This is expected to increase the service level and reduce tardiness, whilst the fuel consumption remains on the original level or reduces (as a result of better fitting of time windows and thus reducing waiting times at both installations and the supply base). As one can see in Tables 51 and 52 this worked in most of the cases, though for schedule 12 all of the parameters remained on the original level, which is most likely the consequence of either the fact that the delay was not significant and the arrival before the expected time as well as tardiness of the vessel to be swapped with were rather sharp or that no swaps at all could have been performed for this schedule. Note that for other schedules the improvements are visually over classing those, achieved by means of other methods, though the detailed multicriteria ranking will be suggested in the ongoing paragraphs.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.919172932	0.003939127	0.000111578	0.919061354	0.91928451	0.89047619	0.004702688	1.39E-04	0.890337393	0.890614988
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.576548663	0.020695804	0.00169903	0.574849634	0.578247693	0.642917067	0.020911365	0.001788788	0.641128279	0.644705855
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.543859649	0.046648775	0.008563354	0.535296295	0.552423003	0.361904762	0.04689702	0.008970294	0.352934468	0.370875056
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.478947368	0.020924123	0.001717774	0.477229595	0.480665142	0.485714286	0.02181288	0.001865905	0.483848381	0.48758019
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
34.46743136	5.839786442	1.07201438	33.39541698	35.53944574	31.46435469	4.918003887	0.940698149	30.52365654	32.40505284
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
35.53930024	5.796685916	1.064102381	34.47519786	36.60340262	31.46435469	4.918003887	0.940698149	30.52365654	32.40505284
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
29.04359261	15.67331499	13.73826632	15.30532629	42.78185893	22.52332479	12.59092133	11.03642915	11.48689564	33.55975394
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
29.25796639	15.79279259	13.84299305	15.41497334	43.10095944	22.52332479	12.59092133	11.03642915	11.48689564	33.55975394
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
22.29814193	13.27163102	4.598385542	17.69975639	26.89652747	14.45546304	9.109581516	3.156308963	11.29915408	17.61177201
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
22.77364868	13.7553768	4.765994905	18.00765377	27.53964358	14.45546304	9.109581516	3.156308963	11.29915408	17.61177201
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
22.50578557	13.13360946	4.550563513	17.95522206	27.05634908	14.58130014	9.183747224	3.18200607	11.39929407	17.76330621
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
22.99283055	13.63425109	4.724026987	18.26880356	27.71685754	14.58130014	9.183747224	3.18200607	11.39929407	17.76330621
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
23.1705801	12.91067528	4.47332076	18.69725934	27.64390086	15.48177748	9.415065549	3.262153781	12.2196237	18.74393126
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
24.04438504	13.79679225	4.780344625	19.26404042	28.82472967	15.96528445	9.447197175	3.273286821	12.69199763	19.23857128
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1044.959183	94.32153827	17.31468204	1027.644501	1062.273865	868.6252818	81.1528322	15.52262275	853.102659	884.1479045
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
65.84830329	5.747757923	1.05512063	64.79318266	66.90342392	69.98523582	6.401748118	1.224503425	68.7607324	71.20973925
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
769.4449899	69.42458149	12.74432729	756.7006627	782.1893172	682.1435117	63.82411227	12.20804734	669.9354644	694.3515591
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
1880.252477	169.4778714	31.11119166	1849.141285	1911.363668	1620.754029	151.3559667	28.9508266	1591.803203	1649.704856
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
9401262.383	847389.3569	155555.9583	9245706.425	9556818.341	8103770.147	756779.8336	144754.133	7959016.014	8248524.28

Table 52. *Estimates of key parameters of schedules 10 in winter (left column) and schedule 12 in summer (right column) after improvement of type 5*

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.825324675	0.005586081	0.00016108	0.825163595	0.825485756	0.968452381	0.002462108	6.80E-05	0.968384406	0.968520356
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.5562208	0.021184867	0.001770518	0.554450281	0.557991318	0.703729945	0.018641089	0.001491598	0.702238347	0.705221543
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0	0	0	0	0	0.75	0.039528471	0.007072541	0.742927459	0.757072541
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.410909091	0.020978899	0.001753305	0.409155786	0.412662396	0.863333333	0.014023129	0.001122084	0.862211249	0.864455417
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
0	0	0	0	0	16.71517762	3.248298655	0.581194373	16.13398325	17.29637199
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
0	0	0	0	0	16.71517762	3.248298655	0.581194373	16.13398325	17.29637199
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
39.20109521	21.91407842	19.20853665	19.99255856	58.40963186	9.278361603	4.807080155	4.213591536	5.064770067	13.49195314
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
41.23601658	23.05163405	20.20564812	21.03036845	61.4416647	9.278361603	4.807080155	4.213591536	5.064770067	13.49195314
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
27.7526356	15.87185835	5.499318348	22.25331725	33.25195395	5.115637897	4.025435969	1.394742405	3.720895492	6.510380301
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
30.70026617	17.58192497	6.091826201	24.60843997	36.79209237	5.159396333	4.021415891	1.393349519	3.766046814	6.552745852
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
27.58808028	15.56515304	5.393050381	22.1950299	32.98113066	4.791242938	3.657107362	1.267123053	3.524119885	6.058365992
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
30.1698344	17.16977962	5.949025125	24.22080928	36.11885953	4.831923883	3.655566986	1.26658934	3.565334543	6.098513223
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
28.69000872	15.79102587	5.471311321	23.2186974	34.16132004	5.190402925	3.651907294	1.265321322	3.925081604	6.455724247
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
31.76376834	17.55007399	6.080790399	25.68297794	37.84455873	5.88194237	5.362424614	1.857985336	4.023957034	7.739927706
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1526.646741	140.0796846	26.1779048	1500.468836	1552.824645	1458.663414	127.7143531	22.85099716	1435.812417	1481.514411
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
65.14384762	5.803215574	1.084497194	64.05935043	66.22834481	93.54639258	7.983027775	1.428344901	92.11804768	94.97473748
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
810.3568917	74.32484711	13.88972839	796.4671633	824.2466201	579.5937838	50.84397841	9.097142003	570.4966417	588.6909258
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2402.14748	220.1919306	41.14917457	2360.998305	2443.296655	2131.80359	186.5325221	33.37490288	2098.428687	2165.178493
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
12010737.4	1100959.653	205745.8729	11804991.53	12216483.27	10659017.95	932662.6103	166874.5144	10492143.44	10825892.47

Table 53. *Estimates of key parameters of schedule 8 in winter (left column) and schedule 7 in summer (right column) after improvement of type 6*

The last method of improvement combines the second and the fifth approaches and thus their benefits and drawbacks, though those of the second approach are expected to dominate over those of the last one. And unfortunately that approach seems to have dominated for schedules 7, 8 and 10, whilst for schedule 12 6th type of improvements managed to combine the two approaches and thus let the 5th approach's influence work well - and as a result costs got significantly reduced with an increased service level. At this stage we can see the possibility of further research in combining improvements of type 4 and 5 so as to both reduce the fuel consumption and reduce the probability of finishing up with worse service levels and/or combining 5th approach with 4th and 2nd simultaneously, so that 4th works only for some vessels whilst 2nd is applied to others and during the swaps not only the schedules but also the speed optimization strategies are reassigned between the vessels, this approach might well lead to the increase of service level combined with the decreased level of fuel consumption, however additional research is needed to either proof or deny the last.

		Winter					Summer		
E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%	E{SS}	s{SS}	ME{SS}	LCI{SS}-95%	UCI{SS}-95%
0.922932331	0.003854286	0.000109175	0.922823156	0.923041506	0.929931973	0.003843848	1.13E-04	0.929818523	0.930045422
E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%	E{SV}	s{SV}	ME{SV}	LCI{SV}-95%	UCI{SV}-95%
0.565307015	0.020763285	0.00170457	0.563602446	0.567011585	0.657036904	0.020717575	0.001772211	0.655264693	0.658809114
E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%	E{PS}	s{PS}	ME{PS}	LCI{PS}-95%	UCI{PS}-95%
0.640350877	0.044946521	0.00825087	0.632100008	0.648601747	0.476190476	0.048739649	0.009322745	0.466867731	0.485513222
E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%	E{PV}	s{PV}	ME{PV}	LCI{SV}-95%	UCI{PV}-95%
0.592982456	0.020577379	0.001689307	0.591293149	0.594671764	0.573333333	0.021585808	0.00184648	0.571486853	0.575179814
E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%	E{TSs}	s{TSs}	ME{TSs}	LCI{TSs}-95%	UCI{TSs}-95%
24.42127904	4.334763203	0.795736032	23.62554301	25.21701507	19.24414817	3.210392816	0.614072426	18.63007575	19.8582206
E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%	E{DSs}	s{DSs}	ME{DSs}	LCI{DSs}-95%	UCI{DSs}-95%
25.35374339	4.304461842	0.790173586	24.5635698	26.14391697	19.43884376	3.20501906	0.613044554	18.8257992	20.05188831
E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%	E{TVs}	s{TVs}	ME{TVs}	LCI{TVs}-95%	UCI{TVs}-95%
23.70978414	13.25417227	11.61779423	12.09198991	35.32757837	13.7209137	7.670223938	6.723247714	6.997665988	20.44416142
E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%	E{DVs}	s{DVs}	ME{DVs}	LCI{DVs}-95%	UCI{DVs}-95%
24.10049292	13.47258512	11.80924153	12.29125139	35.90973445	13.76111367	7.6926964	6.742945696	7.018167969	20.50405936
E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%	E{Ta}	s{Ta}	ME{Ta}	LCI{Ta}-95%	UCI{Ta}-95%
17.75826964	10.21608484	3.539692804	14.21857683	21.29796244	8.833435094	5.3500307	1.853691064	6.97974403	10.68712616
E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%	E{Da}	s{Da}	ME{Da}	LCI{Da}-95%	UCI{Da}-95%
18.48536163	10.87253215	3.767140195	14.71822144	22.25250183	8.939160827	5.372896015	1.861613491	7.077547336	10.80077432
E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%	E{Ts}	s{Ts}	ME{Ts}	LCI{Ts}-95%	UCI{Ts}-95%
17.73639507	10.05350204	3.483360738	14.25303433	21.21975581	8.658272583	5.059305795	1.752960024	6.905312559	10.41123261
E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%	E{Ds}	s{Ds}	ME{Ds}	LCI{Ds}-95%	UCI{Ds}-95%
18.43450902	10.74512958	3.722997456	14.71151157	22.15750648	8.758225554	5.078397715	1.759575036	6.998650518	10.51780059
E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%	E{Td}	s{Td}	ME{Td}	LCI{Td}-95%	UCI{Td}-95%
18.90172242	9.887412762	3.42581374	15.47590868	22.32753616	9.429059456	4.973515787	1.723235302	7.705824154	11.15229476
E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%	E{Dd}	s{Dd}	ME{Dd}	LCI{Dd}-95%	UCI{Dd}-95%
20.02930934	10.69563525	3.705848545	16.3234608	23.73515789	10.07751859	5.670273092	1.964649392	8.112869201	12.04216798
E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%	E{Sfc}	s{Sfc}	ME{Sfc}	LCI{Sfc}-95%	UCI{Sfc}-95%
1373.558817	124.1035764	22.78179516	1350.777022	1396.340612	1061.376906	99.27593615	18.98914509	1042.38776	1080.366051
E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%	E{Bfc}	s{Bfc}	ME{Bfc}	LCI{Bfc}-95%	UCI{Bfc}-95%
65.10206746	5.678001003	1.042315295	64.05975216	66.14438275	71.98451308	6.605427173	1.263462425	70.72105065	73.2479755
E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%	E{Ifc}	s{Ifc}	ME{Ifc}	LCI{Ifc}-95%	UCI{Ifc}-95%
795.41752	71.71014995	13.16389096	782.2536291	808.581411	613.7256736	57.43286152	10.98555181	602.7401218	624.7112254
E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%	E{Tfc}	s{Tfc}	ME{Tfc}	LCI{Tfc}-95%	UCI{Tfc}-95%
2234.078404	201.4588751	36.98197071	2197.096434	2271.060375	1747.087092	163.2790471	31.23143066	1715.855662	1778.318523
E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%	E{TCf}	s{TCf}	ME{TCf}	LCI{TCf}-95%	UCI{TCf}-95%
11170392.02	1007294.376	184909.8536	10985482.17	11355301.88	8735435.461	816395.2354	156157.1533	8579278.308	8891592.614

Table 54. *Estimates of key parameters of schedules 10 in winter (left column) and schedule 12 in summer (right column) after improvement of type 6*

In Tables 55(a) and 55(b) presented below one can see that in the majority of the outcomes (83.33%) improvements gave a significant increase in the final ranking of the corresponding schedule and if not considering cost-focused experiments this percentage achieves 95.83% percent. This means that all of the suggested improvements in general are indeed profitmaking in terms of robustness versus fuel consumption. Unfortunately, from the sample of experiments carried out it is rather difficult to say which exactly improvement is the best one and which one is the worst one, since their efficiency is very much dependent on the characteristics of the very schedule addressed. Although we might well say that e.g. for schedule 7 in summer season improvement 1 would be the best one, 5 is the second best 6 is the third best and etc.; the same logic can be applied to every schedule, the improvements were tested on. All the details are presented in Tables 55(a) and 55(b).

Schedule	Exp 1	Exp 2	Exp 3	Exp 4	SPH Exp
Schedule12-S-10304-S 3	0.299534	0.172453	0.165998	0.17914	0.049723
Schedule7-S-10344-B 1	0.245765	0.149202	0.127531	0.252484	0.058758
Schedule7-S-10344-B 5	0.291519	0.216113	0.146871	0.284236	0.101244
Schedule12-S-10304-S 6	0.331444	0.326795	0.154282	0.173435	0.131058
Schedule7-S-10344-B	0.329435	0.256563	0.198698	0.330989	0.159815
Schedule7-S-10344-B 2	0.277387	0.166728	0.180316	0.395748	0.166854
Schedule7-S-10344-B 6	0.281698	0.161004	0.174677	0.400609	0.168952
Schedule7-S-10344-B 3	0.265008	0.169456	0.179321	0.413306	0.176937
Schedule9-S-10344-W	0.41377	0.239267	0.22348	0.31858	0.184601
Schedule12-S-10304-S 2	0.411226	0.358003	0.251954	0.278248	0.216625
Schedule11-S-10344-S	0.420331	0.331108	0.324729	0.229008	0.22195
Schedule7-S-10344-B 4	0.390926	0.29176	0.297722	0.366027	0.236178
Schedule10-W-10344-R 3	0.390597	0.278082	0.311505	0.451418	0.278741
Schedule12-S-10304-S 1	0.487259	0.427402	0.353825	0.235177	0.290951
Schedule12-S-10304-S	0.481456	0.4364	0.36597	0.24278	0.298426
Schedule12-S-10304-S 5	0.505618	0.475651	0.39003	0.260479	0.332733
Schedule6-S-10304-R	0.410727	0.608192	0.337266	0.232119	0.337356
Schedule5-S-10304-B	0.509677	0.416534	0.384193	0.466882	0.384821
Schedule10-W-10344-R 4	0.527751	0.477547	0.487974	0.338723	0.399136
Schedule10-S-10344-R	0.568477	0.451947	0.511104	0.35914	0.416988
Schedule10-W-10344-R 2	0.492266	0.348092	0.48986	0.583784	0.448743
Schedule10-W-10344-R 6	0.488457	0.373638	0.492121	0.598248	0.462937
Schedule12-W-10304-S	0.593381	0.596287	0.508721	0.351067	0.465667
Schedule10-W-10344-R 5	0.586894	0.458663	0.59387	0.435779	0.48308
Schedule12-S-10304-S 4	0.655232	0.624172	0.575652	0.379856	0.519794
Schedule7-W-10344-B	0.588033	0.474718	0.540493	0.61247	0.541919
Schedule9-W-10344-W	0.659974	0.488096	0.544798	0.605515	0.558076
Schedule5-W-10304-B	0.605499	0.569028	0.519644	0.592175	0.561091
Schedule8-S-10304-W	0.466269	0.75275	0.641487	0.440212	0.569687
Schedule11-W-10344-S	0.626859	0.564269	0.650054	0.52073	0.581162
Schedule8-W-10304-W 4	0.478332	0.764991	0.68392	0.458703	0.597517
Schedule10-W-10344-R	0.658936	0.552006	0.714901	0.522504	0.604247
Schedule8-W-10304-W 5	0.473776	0.757888	0.702596	0.478163	0.609706
Schedule10-W-10344-R 1	0.624668	0.507753	0.75157	0.56028	0.612116
Schedule6-W-10304-R	0.589158	0.781424	0.700538	0.504681	0.648856
Schedule8-W-10304-W 1	0.500319	0.800761	0.753896	0.528488	0.665554
Schedule8-W-10304-W	0.523321	0.827816	0.814906	0.576576	0.717683
Schedule8-W-10304-W 3	0.49536	0.76233	0.645707	0.758007	0.72121
Schedule8-W-10304-W 2	0.517113	0.826659	0.798601	0.844382	0.840691
Schedule8-W-10304-W 6	0.544512	0.899327	0.937366	0.923277	0.920393

Table 55(a). *TOPSIS ranking of the schedules with improvements and without them, summer and winter seasons are considered separately*

The aggregated ranking above (Table 55(b)) considers the improvements applied for half of the year only, whereas the other half of the year for the corresponding schedules is considered without improvements, this is so, since we only had the improvements tested on any particular schedule for half of the year run of the simulation in order to reduce the amount of experiments and simultaneously manage to cover all four speed optimization strategies (see Tables 43-54). The last leads to the fact that in Table 55(b) improvements might be slightly underestimated for those cases they are profitmaking in both seasons and/or overestimated for those cases when they are loss making in both seasons (in comparison to the case when having them applied for both of the seasons) when the final ranking appears, the situation when some improvement is profitmaking in one season but lossmaking in the other also cannot be analyzed basing on the Table above. Note, that seasons for which improvements are applied are shown in brackets after improvements' type.

Alternative	Aggr. RC value
Schedule12-10304-S 3(S)	0.235947094
Schedule7-10344-B 1(S)	0.262001898
Schedule12-10304-S 6(S)	0.270377515
Schedule7-10344-B 5(S)	0.286841802
Schedule7-10344-B 2(S)	0.32353831
Schedule7-10344-B 6(S)	0.324307373
Schedule7-10344-B	0.325882428
Schedule7-10344-B 3(S)	0.329419911
Schedule12-10304-S 2(S)	0.337342043
Schedule9-10344-W	0.355157491
Schedule7-10344-B 4(S)	0.385324475
Schedule12-10304-S 1(S)	0.396189704
Schedule11-10344-S	0.398061087
Schedule12-10304-S	0.402806921
Schedule10-10344-R 3(W)	0.420524048
Schedule12-10304-S 5(S)	0.431747978
Schedule10-10344-R 4(W)	0.46674509
Schedule10-10344-R 2(W)	0.488346807
Schedule10-10344-R 6(W)	0.496051331
Schedule10-10344-R 5(W)	0.50592005
Schedule5-10304-B	0.516847641
Schedule6-10304-R	0.528366044
Schedule12-10304-S 4(S)	0.573697972
Schedule10-10344-R	0.574076858
Schedule10-10344-R 1(W)	0.578042632
Schedule8-10304-W 4(W)	0.664921877
Schedule8-10304-W 5(W)	0.672523994
Schedule8-10304-W 1(W)	0.70617585
Schedule8-10304-W	0.738270397
Schedule8-10304-W 3(W)	0.741899602
Schedule8-10304-W 2(W)	0.811386082
Schedule8-10304-W 6(W)	0.850406679

Table 55(b). *TOPSIS ranking of the schedules with improvements and without them, summer and winter seasons are considered together*

In order to sum the content of this chapter up we should notice that in general evaluated schedules have a rather high service level, though some of them have slightly better performance whilst other have slightly worse performance, some of them are slightly cheaper, whilst some of them are more expensive (see the corresponding to schedules Tables and aggregated Tables 41(a, b), 42(a, b), 55(a, b) with schedules' rankings). Both average tardiness of the visits and/or ending of voyages and schedules in the majority of occasions creates more than 50% of the corresponding deviations of scheduled times, which means that visits are delayed in more cases than performed before scheduled time. Even though, in case tardiness related parameters are smaller than the corresponding deviations, then sometimes the corresponding service is completed in time: in particular if we regard to tardiness and deviations of voyages (schedules) then in case tardiness is lower than deviations then there is a certain percentage of voyages (schedules) completed in time. If however average tardiness of some voyages (schedules) is equal (or close) to zero then all of the visits are performed in time or in advance then the corresponding parameters describing completion of voyages (schedules) becomes 100% (almost 100%) and deviations show only how badly utilized these schedules are. Obviously the ideal schedule would have both deviations and tardiness close to zero, which in turn would provide all service-level related parameters be close to 1 and simultaneously let the installations and supply basses be serviced right in time. Differences between deviations and tardiness of arrival, discharge and departure times might be used for the analysis of waiting times and lengthening of service times at the locations and are highly correlated with changes of fuel consumptions at the corresponding locations, meaning that if average tardiness and deviations of arrival are equal to these parameters of discharge and departure then the service itself was performed as scheduled and no additional waiting time on average was needed. What concerns sailing fuel consumptions, it must be mentioned that they might only be violated in case durations of voyages increase or decrease, though their marginal values only depend on engine speed of vessels and do not change in case no improvements are applied.

We have suggested 6 types of a posteriori improvements, which, as shown above, in general work very well. Here, however, we will try to describe their properties and mention their "target schedules".

The first improvement only utilizes slacks between the voyages for not tardy voyages and by that creates additional slack for the beginning of the next voyage, which is aimed to increase all service level related parameters and decrease average tardiness (most likely not by much, since time windows might well become violated and positive effect might well get dispersed soon enough, which by the way also explain why schedules with 4-hours slack incorporated at the beginning or end of schedules do not always outrank equivalent schedules without it by much), however this improvement might well also increase deviations unless this effect gets dispersed, the positive thing is that the improvements caused by it will not in turn cause increase of fuel consumption in the majority of outcomes, the main drawback in addition to the fact, that the positive effect gets dispersed in most of occasions, is that this improvement is hardly implementable in practice, since the departures from the supply base depend on onshore logistics very much, whilst the last is assigned to the planned departure times.

The second improvement is aimed to minimize both tardiness and deviations of all visits (and thus service level) without significant increase of fuel consumptions, though the last only works in cases vessels are delayed approximately the same amount of times and by the same time and as being going in advance of their schedule, which does not seem to hold on the given set of schedules, which means that not only tardiness and deviations decrease and service level increase but also fuel consumptions do slightly increase. A perfect schedule for this type of improvements is the one that has tardiness creating around half of the corresponding deviations or less.

The third type of improvements is only aimed to minimize the tardiness and thus in general has a better effect on the service level than the previous one, however it also provokes significant increase of fuel consumption, and thus an ideal schedule for this type of improvement is the one that already has a rather low tardiness, with improvement aimed to achieve an even better estimate or/and the one, which urgently needs this parameter as low as possible and for which fuel consumption does not matter much.

The fourth type of improvements on the contrary aims to reduce fuel consumptions for schedules without a significant loss of service level and increase of tardiness. This improvement works perfect for badly utilized schedules with too much slack on the legs, however for schedules with both high tardiness and deviations it might well provide loss of service level on average due to reducing slacks on the legs when a vessel sails in advance and doing nothing at those legs when a vessel is being late, which might even happen during the same voyage in case a schedule is constructed with no stochasticity considered.

The fifth type of improvement is rather similar to the first one in terms of waiting slack at the supply base utilization; however it does not violate time windows at the installations by that much and thus has a lower probability of getting dispersed soon. This approach is aimed to reduce tardiness and thus increase service levels without increase of fuel consumption moreover it does not have a drawback connected to dependence on onshore logistics. Though it only works if there is a subset of vessels which are delayed and another subset of those, which go in advance of their schedules. This type of improvement has proved to be a very efficient one for schedules, where these subsets appear.

The sixth type of improvements is aimed to combine benefits and drawbacks of second and fifth types of improvements. However in practice in most of the occasions second type of improvements dominates over the fifth and thus all its benefits are achieved, whilst the drawbacks are only slightly reduced as a result of tardiness utilization by means of the improvements of fifth type. Also note that this improvement might only sometimes work significantly better than any of the improvements it combines.

So, as one can see, most of the improvements might be wisely chosen basing on the characteristics of the schedules; however the most just way to choose the best improvement for a given schedule still remains the option to simulate all of them and afterwards choose the most beneficial by means of multicriteria ranking suggested.

7. Conclusions

Offshore installations need supply vessel services on a regular basis. Weekly vessel plans are constructed in order to manage this service. Construction of these schedules is complicated by a great deal of constraints and requirements of different nature (limited durations of voyages, fixed departures from a supply base, spread of departures to installations, limited capacities of vessels, presence of working hours at the installations and etc). Moreover weather uncertainty impacts on how service is performed. Several simplifications and assumptions are often made when constructing the schedules. In reality with weather uncertainty this might lead to violation of some important characteristics of the schedules such as service level and fuel consumptions. However different robustness and speed optimization strategies are generally incorporated into constructing of supply vessel schedules in order to increase robustness of schedules and reduce their emissions.

In the course of research several problems were resolved by means of both adopting several known techniques and developing our own approaches:

1. Advanced statistical data analysis for weather modelling was performed by means of k-means clustering and analysis of statistical distributions and stochastic processes of significant wave heights and wave directions.

2. The algorithm for ARIMA based weather simulation and forecasts of the simulated weather that simultaneously takes into account several weather parameters in several clusters and the correlations between the time series was suggested, implemented and used on real models for the corresponding weather parameters.

3. Once weather models were constructed, a discrete event based simulation model for vessel schedules was built in Arena simulation software with respect to the modeled weather simulations and forecasts incorporated.

4. When having this tool developed a new exact algorithm for calculation of sailing time between any pairs of location with respect to weather stochasticity and weather clusters' crossing was suggested and implemented, in addition we suggested and implemented a simplified approximate solution for this problem.

5. A set of robustness criteria such as estimators for mathematical expectation, standard deviation, and confidence intervals of service level, tardiness and deviations from expected arrival, discharge and departure times as well as fuel consumptions and fuel costs were suggested as quality of schedule criteria. The source code for their estimation was developed and integrated with the simulation tool.

6. An aggregated measure of quality-focused criteria was suggested and implemented, basing on our own adaptation of TOPSIS algorithm.

7. A set of a posteriori improvements of schedules were suggested and incorporated into the simulation tool.

8. A set of weekly schedules were evaluated basing on outputs of the simulation tool and ranked with respect to the adopted multicriteria ranking tool.

9. Suggested a posteriori improvements proved their efficiency on a sample from the given schedules and thus considered as highly potential in real practice.

The developed tool was used for evaluation of schedules constructed with different robustness and speed optimization strategies and their comparison. In total experiments were conducted on twelve schedules, which differ in a number of installations, vessels, added slacks and speed optimization strategies applied. This simulation was carried out on an annual time horizon, divided into summer and winter seasons.

The results of experiments show that all schedules perform significantly worse in winter periods in comparison to summer periods, which means that they are quite sensitive to weather conditions.

On the set of instances, based on five installations serviced by one vessel, the best aggregated performance among schedules in winter is worse than the worst performance in summer. The schedule generated without speed optimization is the best in terms of robustness-related parameters, however it is significantly worse than the schedules constructed with speed optimization on voyage legs in terms of fuel consumption. The schedule constructed with speed optimization on voyage legs with waiting time shows the best performance in terms of robustness versus fuel consumption, it performs stably in both winter and summer seasons, and thus is considered as the best schedule on this set of schedules in terms of its multicriteria performance. The schedule based on sequential speed optimization on voyage legs has a poorer performance in terms of robustness versus fuel consumption. The schedule based on recursive speed optimization strategy is considered to be the worst schedule on a given set because of its relatively low service level in both summer and winter seasons, provoked by high tardiness, moreover it has rather high fuel consumption.

On instances with ten installations serviced by two vessels all schedules perform significantly better in summer than in winter. Moreover, in more than 90% of cases the worst summer performance is better than the best performance in winter. Basing on this sample of schedules we might also note that in 75% of the outcomes schedules with slack overperform those without slack in terms of robustness versus fuel consumption with the only exception for schedules built with recursive speed optimization, which perform similarly. Results of tests on these instances show that sequential speed optimization strategy performs best in terms of robustness versus fuel consumption, whilst recursive speed optimization strategy shows the worst results. The schedules constructed with design speed and those with speed optimization on voyage legs with waiting time, both having good performance in terms of service but rather high fuel consumption, with the first one over performing the second one.

On both groups of instances, the schedules based on recursive speed optimization strategy perform worst in terms of robustness versus fuel consumption. It is however more difficult to objectively rank other speed optimization strategies since they perform differently on two groups of instances.

Four schedules from the last group of instances were chosen for a posteriori improvements. These improvements in general occurred to be beneficial in the majority of outcomes. Basing on the results of the experiments it is difficult to find a correspondence between the best type of improvements for a particular speed optimization strategy. Although it is possible to say for which types of parameters of schedules particular improvements are beneficial.

Thus, improvements with waiting slack utilization at the supply base in some occasions reduce tardiness and increase service level without significant increase of fuel consumption they also increase deviations. However this type of improvements only works for schedules without tardiness of at least some voyages, moreover the effect of the improvement might well be dispersed because of time windows at the installations. Improvements that adjust the speed to minimize deviation of departure time significantly reduce deviations and tardiness and increase service level, however in case most of the deviations are created by tardy visits; this type of improvements also leads to significant increase in fuel consumption. Improvements aimed to decrease tardiness of voyages improve service level of schedules, however for schedules with a high percentage of tardiness in the deviations it provokes an indeed significant increase of fuel consumptions. Improvements that minimize deviations leading to early departures on the contrary reduce fuel consumptions without a significant loss of service level and significant increase of tardiness. This type of improvements works well for schedules with low utilization of slacks. Improvements with swaps of delayed and shortened voyages between the corresponding vessels are aimed to reduce tardiness and increase service level without any increase of fuel consumption, though this only works when there exist such voyages. The mixed improvement that combines the improvement that adjusts the speed to minimize deviation of departure time and improvements mentioned in the previous paragraph also combines benefits and drawbacks of them, however benefits and drawbacks of the first one dominate in the majority of the outcomes.

Thus, practical contribution of the research is evaluation of schedules' performance as well as comparative analysis of speed optimization strategies and results of a posteriori schedules' improvements. The scientific contribution of this research includes the simulation model for weekly supply vessel schedules evaluation and improvements, advanced statistical analysis of weather at the Norwegian continental shelf, implementation of algorithms for routing of vessels in multi cluster weather environment, implementation of simulation algorithms for auto correlated and correlated between each other stochastic processes of weather parameters, and adaptation of multicriteria ranking algorithm for evaluation of schedules.

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Appendix A

Listing A-1. *Wolfram Mathematica script for statistical distributions analysis of SWH*

```
ClearAll;
Data = Take[Import["C:\\studies\\himolde\\year 2\\Simulational
Modelling\\Distributions\\AggregatedData1.csv"]];
n=5;
m=52;
MeanStds= Table[0,{j,1,2},{i,1,n}];
Headers = Transpose[Take[Data,1]];
For[i=1,i<=m,i++,
For[j=1,j<=n, j++,
Data1 =  Transpose[Take[Data,{(i-1)*55+2,i*55+1},{j+2,j+2}]][[1]];
Print[StringJoin["Installation ",ToString[Headers[[j+2]]],"; Week ",ToString[i],":"]];
Print[dist=EstimatedDistribution[Data1,GammaDistribution[alpha,beta]]];
Print[DistributionFitTest[Data1,dist,{"TestDataTable",All}]];
Print["Autocorrelation Function: "];
Print[Show[Plot[{0.7,-0.7},{x,0,50}],ListPlot[CorrelationFunction[Data1,{50}]]]]];
Print["Histogram and Fitted Distribution: "];
Print[Show[Histogram[Data1,"FreedmanDiaconis","Probability"],Plot[PDF[dist,x],{x,0,10}]]];
Print["Mean/Std = ",MeanStds[[1,j]]=Mean[dist]];
MeanStds[[2,j]]=Headers[[j+2]];
If[j==n,
Print["Clusters for week ",ToString[i]];
Print[MatrixForm[clusters=FindClusters[MeanStds[[1]]->MeanStds[[2]]]]];
];
Clear[alpha,beta,Data1,dist];
];
];
Quit[];
```

Listing A-2. *Sample of VBA code for importing *csv files*

```
Open "vessels.csv" For Input As #1
  row_number = 0
  Line Input #1, LineFromFile
  LineItems = Split(LineFromFile, ";")
  If LineItems(0) = "#" Then
    Line Input #1, LineFromFile
    LineItems = Split(LineFromFile, ";")
  End If
  s = CInt(LineItems(0))
  v_vessnum = s
  ReDim v_dweight(s – 1) As Double
  ReDim v_flag(s – 1) As Boolean
  ReDim v_capacity(s – 1) As Double
  ReDim v_costs(s – 1, 3) As Double
  ReDim v_vname(s – 1) As String
  Line Input #1, LineFromFile
  For i = 1 To s
    Line Input #1, LineFromFile
    LineItems = Split(LineFromFile, ";")
    If LineItems(1) = "#" Then
      Line Input #1, LineFromFile
      LineItems = Split(LineFromFile, ";")
    End If
  v_flag(i – 1) = False
  v_dweight(i – 1) = val(LineItems(2))
```

```
v_capacity(i – 1) = val(LineItems(3))
v_vname(i – 1) = LineItems(0)
v_costs(i – 1, 0) = val(LineItems(5))
v_costs(i – 1, 1) = val(LineItems(6))
v_costs(i – 1, 2) = val(LineItems(7))
v_costs(i – 1, 3) = val(LineItems(8))
Next i
Close #1
```

Listing A-3. *C# source code for ARIMA based weather simulation and forecasting.*

```
 public class Program
{
    enum Transformation : byte { D1, D2, LD1, LD2, Other};
    enum ResidualDist : byte { Normal, LogNormal, TDisr, other};
    enum WParam : byte { Wheight, WDir, Other};
    private class ARIMA
    {
        public ARIMA()
        {
            ar = null;
            ma = null;
            shour = fhour = 0;
        }
        public ARIMA(double [] AR, double [] MA,double C, int sh, int fh, int tpe, int clust, ResidualDist rd, double
mean, double std, Transformation trans, double [,,][] mWeather, int hor )
        {
            ar = (double [])AR.Clone();
            ma = (double [])MA.Clone();
            intercept = C;
            shour = sh;
            fhour = fh;
            type = type = (tpe == 0)?WParam.Wheight : (tpe == 1)? WParam.WDir : WParam.Other;
            cluster = clust;
            resdistr = rd;
            resmean = mean;
            resstd = std;
            datatransf = trans;
            data = new List<double>[2];
            Console.WriteLine();
            name = "ARIMA (" + sh + ";" + fh + ";" + tpe + ";" + clust + ";" + ")";
            Console.WriteLine("Add ARIMA (" +sh + ";" + fh + ";" + tpe + ";" + clust + ";"+")"  );
            TranformData(mWeather,hor);
        }

        public double CalculateArimaSim(int tID, ref double [,,][] mWeather, double SNN, int N)
        {
            if ((data[0].Count < tID))
                throw new Exception("No Data available for Such a Time");
            Console.WriteLine("Simulating of "+name);
            int hor = Math.Max(ma.Length, ar.Length);
            double res = intercept;

            for(int i = 0; i < ar.Length; i++)
            {
                res += data[0][tID – 1 – i]*ar[i];
            }
            for(int i = 0; i < ma.Length; i++)
            {
```

```
               res += data[1][tID – 1 – i]*ma[i];
            }

            double resid = GenerateResidual(100,SNN);

            res += resid;
            data[0].Add(res);
            data[1].Add(resid);
            double simulated = InvertTransformData(tID,ref mWeather);
            mWeather[(int) type, tID, 0][cluster] = simulated; //??
            mWeather[(int)type, tID, 1][cluster] = resid;

            return simulated;
         }
         public double CalculateArimaForecast(int tID, ref double [,,][] mWeather, double realvalue)
         {
            if((data[0].Count<tID))
               throw new Exception("No Data available for Such a Time");
            Console.WriteLine("Forecasting of " + name);
            double res = intercept;

            for(int i = 0; i < ar.Length; i++)
            {
               res += data[0][tID – 1 – i]*ar[i];
            }
            for(int i = 0; i < ma.Length; i++)
            {
               res += data[1][tID – 1 – i] * ma[i];
            }
            TranformPair(mWeather,tID);
            double resid = data[0][tID] – res;
            data[1].Add(resid);
            return InvertTransformData(tID, ref mWeather);
         }
         public double InvertTransformData(int ID, ref double [,,][] mWeather)
         {
             switch (datatransf)
             {
                case Transformation.LD1:
                   {
                      return Math.Exp(data[0][ID – 1])*mWeather[(int) type, ID – 1, 0][cluster];
                      break;
                   }
                   ;
                case Transformation.D1:
                   {
                      return data[0][ID] + mWeather[(int) type, ID – 1, 0][cluster];
                      break;
                   }
                case Transformation.D2:
                   {

                      return data[0][ID – 2] + 2*mWeather[(int) type, ID – 1, 0][cluster] – mWeather[(int) type, ID – 2,
0][cluster];
                      break;
                   }
             }
            return -1;
         }
         private double GenerateResidual(int CLT_Length, double resid)
```

```
{
   resid /= CLT_Length;
   resid = (resid – 0.5)/Math.Sqrt(1.0/(12.0*((double)CLT_Length)));

   resid = resid*resstd + resmean;

   return resid;
}
private void TranformPair(double[, ,][] mWeather, int i)
{

   switch (datatransf)
   {
      case Transformation.LD1:
         {


            data[0].Add(
               Math.Log(mWeather[(int)type, i, 0][cluster]) -
                     Math.Log(mWeather[(int)type, i – 1, 0][cluster]));
            data[1].Add(mWeather[(int)type, i, 1][cluster]);

            break;
         }

      case Transformation.D1:
         {

            data[0].Add
               (mWeather[(int)type, i, 0][cluster] -
                     mWeather[(int)type, i – 1, 0][cluster]);
            data[1].Add(mWeather[(int)type, i, 1][cluster]);

            break;
         }
      case Transformation.D2:
         {


            data[0].Add
               (mWeather[(int)type, i, 0][cluster] -
                     2 * mWeather[(int)type, i – 1, 0][cluster] + mWeather[(int)type, i – 2, 0][cluster]);
            data[1].Add(mWeather[(int)type, i, 1][cluster]);

            break;
         }
   }
}
private void TranformData(double [,,][] mWeather, int hor)
{
   data[0] = new List<double>();
   data[1] = new List<double>();

   switch (datatransf)
   {
      case Transformation.LD1:
         {
            data[0].Add(0);
            data[1].Add(0);
            for(int i = 1; i< hor;i++)
            {
```

```
                    data[0].Add(
                        Math.Log(mWeather[(int) type, i , 0][cluster]) -
                                Math.Log(mWeather[(int) type, i-1, 0][cluster]));
                    data[1].Add(mWeather[(int) type, i, 1][cluster]);
                }
                break;
            }

        case Transformation.D1:
            {
                data[0].Add(0);
                data[1].Add(0);
                for(int i = 1; i< hor;i++)
                {
                    data[0].Add
                        (mWeather[(int) type, i , 0][cluster] -
                                mWeather[(int) type, i -1, 0][cluster]);
                    data[1].Add(mWeather[(int) type, i, 1][cluster]);
                }
                break;
            }
        case Transformation.D2:
        {
            data[0].Add(0);
            data[1].Add(0);
            data[0].Add(0);
            data[1].Add(0);
            for(int i = 2; i< data[0].Count;i++)
                {
                    data[0].Add
                        (mWeather[(int) type, i, 0][cluster] -
                                2*mWeather[(int) type, i-1, 0][cluster] + mWeather[(int) type, i-2, 0][cluster]);
                    data[1].Add(mWeather[(int) type, i , 1][cluster]);
                }
                break;
        }
    }
}
private List<double>[] data;
public List<double>[] Data
{
    get { return data; }
    set { data = value; }
}
private string name;
public string Name
{
    get { return name; }
    set { name = value; }
}

private double[] ar;
public double [] AR
{
    get { return ar; }
    set { ar = value; }
}
private double[] ma;
public double [] MA
{
```

```
        get { return ma; }
        set { ma = value; }
    }
    private int shour;
    public int Shour
    {
        get { return shour; }
        set { shour = value; }
    }
    private int fhour;
    public int Fhour
    {
        get { return fhour; }
        set { fhour = value; }
    }
    private double intercept;
    public double Intercept
    {
        get { return intercept; }
        set { intercept = value; }
    }
    private double resstd;
    public double ResStd
    {
        get { return resstd; }
        set { resstd = value; }
    }

    private double resmean;
    public double ResMean
    {
        get { return resmean; }
        set { resmean = value; }
    }
    private int cluster;
    public int Cluster
    {
        get { return cluster; }
        set { cluster = value; }
    }
    private WParam type;
    public int WType
    {
        get { return (int)type; }
        set { type = (value==0)?WParam.Wheight : (value == 1)? WParam.WDir : WParam.Other; }
    }
    private ResidualDist resdistr;
    public  ResidualDist Resdistr
    {
        get { return resdistr; }
        set{ resdistr = value;}
    }

    private Transformation datatransf;
    public  Transformation Datatransf
    {
        get { return datatransf; }
        set{ datatransf = value;}
    }
}
```

```
static public int sHour;
static public int fHour;
static public int tCount;
static public int[,] mCount;
static public int[] tClusters;
static public double[, ,][] mWeather;
static private List<ARIMA>[][] VARIMA;
static public int horizon;
static public Random rand;
static public double generateSNN(int CLT_Length)
{

    double resid = 0;
    for (int i = 0; i < CLT_Length; i++)
    {
        resid += rand.NextDouble();
    }
    return resid;
}
static public void weatherModelling(string dName)
{
    DirectoryInfo wDir = new DirectoryInfo(dName);
    rand = new Random();
    FileInfo gFile = new FileInfo(dName + @"\common.dat");
    StreamReader gRead = gFile.OpenText();
    gRead.ReadLine();
    string[] sData = gRead.ReadLine().Split('\t');
    sHour = int.Parse(sData[0]);
    fHour = int.Parse(sData[1]);
    tCount = int.Parse(sData[2]);
    tClusters = new int[tCount];
    string[] tpes = sData[3].Split(';');
    VARIMA = new List<ARIMA>[tCount][];

    for (int i = 1; i <= tCount; i++)
    {

        tClusters[i – 1] = int.Parse(tpes[i-1]);
        VARIMA[i – 1] = new List<ARIMA>[tClusters[i – 1]];
        VARIMA[i – 1] = new List<ARIMA>[tClusters[i – 1]];
        for(int j = 0;j<tClusters[i – 1];j++)
        {
            VARIMA[i – 1][j] = new List<ARIMA>();
            VARIMA[i – 1][j] = new List<ARIMA>();
        }
    }
    mWeather = new double[tCount,(fHour-sHour) +1 + horizon,2][];
    ReadHistoricalWeather(dName);
    gRead.ReadLine();
    while(!gRead.EndOfStream)
    {
        string tmp = gRead.ReadLine();
        sData = tmp.Split('\t');
        AddArimaModel(sData);
    }
    gRead.Close();
    RunModels();
    WriteModelledWeather(dName);
}
public static int N = 100;
```

```
static public void RunModels()
{
   for(int i = horizon;i<= horizon + fHour-sHour; i++)
   {
      Console.WriteLine("Weather is Simulated for period "+(sHour+i-horizon) +" with ID " + i);
      double SNN = generateSNN(N);
      foreach (var arimacl in VARIMA)
      {
         foreach (var arimalist in arimacl)
         {
            foreach (var arima in arimalist)
            {
               if(arima.Shour<=i-horizon+sHour && arima.Fhour>=i-horizon+sHour)
               {
                  arima.CalculateArimaSim(i,ref mWeather,SNN,N);
               }

            }
            foreach (var arima in arimalist)
            {
               if(!(arima.Shour<=i-horizon+sHour && arima.Fhour>=i-horizon+sHour))
                  arima.CalculateArimaForecast(i, ref mWeather,mWeather[(int)arima.WType,i,0][arima.Cluster]);

            }
         }
      }
   }
}
static public void WriteModelledWeather(string dName)
{
   Console.WriteLine("Writing results");
  TextWriter write = new StreamWriter(dName+@"\modelled_weather.dat");
  for(int i = horizon-1;i<horizon + fHour-sHour+1;i++)
  {
     if(i!=horizon-1)
        write.Write(sHour + i – horizon + "\t");
     else
     {
        write.Write("No" + "\t");
     }
      for(int j = 0; j<tCount;j++)
      {
         for(int k = 0; k<tClusters[j];k++)
         {

               if (i == horizon -1)
               {
                  write.Write(((j == 0) ? "W_H" : (j == 1) ? "W_DX" : "W_DY") + ":CL-" + k + ":Val" + "\t");
                  write.Write(((j == 0) ? "W_H" : (j == 1) ? "W_DX" : "W_DY") + ":CL-" + k + ":Res" + "\t");
               }
               else
               {
                  write.Write(mWeather[j,i,0][k]+"\t");
                  write.Write(mWeather[j, i, 1][k] + "\t");
               }
         }
      }
     write.WriteLine();
  }
   write.Close();
```

```
}
static public void ReadHistoricalWeather(string dName)
{
   Console.WriteLine("Reading Data");
   StreamReader readData = new StreamReader(dName + @"\WeatherData.dat");
   readData.ReadLine();
   int cl = 0;
   int tp = 0;
   int hh = 0;
   int curH = 0;
   int histS = (sHour – horizon >= 0) ? sHour – horizon : 2928 – (horizon – sHour);
   int histF = (sHour – 1 >= 0) ? sHour – 1 : 2927;

   while(!(readData.EndOfStream))
   {
      string[] tmp = readData.ReadLine().Split('\t');
      if (histS < fHour)
      {
         if (curH < histS)
         {
            curH++;
            continue;
         }
         if (curH == histS)
         {
            hh = 0;

         }
         if(curH>fHour)
            break;
      }
      if(histS > fHour)
      {
         if(curH>fHour&&curH<histS)
         {
            curH++;
            continue;
         }
         if (curH == histS)
            hh = 0;
         if (curH == 0 && histF < sHour)
         {
            hh = horizon – histF – 1;
         }

      }
      if (curH == sHour)
         hh = horizon;

      cl = 0;
      tp = 0;

      mWeather[tp, hh, 0] = new double[tClusters[tp]];
      mWeather[tp, hh, 1] = new double[tClusters[tp]];
      for(int i = 1; i<tmp.Length; i=i+2)
      {

         mWeather[tp, hh,0][cl] = double.Parse(tmp[i]);
         mWeather[tp, hh,1][cl] = double.Parse(tmp[i + 1]);
         cl++;
```

```
          if(cl==tClusters[tp]&&tp+1<tCount)
          {
            cl = 0;
            tp++;
            mWeather[tp, hh, 0] = new double[tClusters[tp]];
            mWeather[tp, hh, 1] = new double[tClusters[tp]];
          }
        }

        hh++;
        curH++;
      }

      readData.Close();
    }
    static public void AddArimaModel(string[] sData)
    {

      int type = int.Parse(sData[0]);
      int cluster = int.Parse(sData[1]);
      int sh = int.Parse(sData[2]);
      int fh = int.Parse(sData[3]);
      int transf_type = int.Parse(sData[4]);
      Transformation trans = (transf_type == 0)
                    ? Transformation.D1
                    : (transf_type == 1)
                       ? Transformation.D2
                       : (transf_type == 2)
                          ? Transformation.LD1
                          : (transf_type == 0)
                             ? Transformation.LD2
                             : Transformation.Other;

      string[] sAR = sData[5].Split(';');
      string[] sMA = sData[6].Split(';');
      double [] AR = new double[sAR.Length];
      double [] MA = new double[sMA.Length];
      for(int i = 0; i<sAR.Length;i++)
      {
        AR[i] = double.Parse(sAR[i]);
      }
      for (int i = 0; i < sMA.Length; i++)
      {
        MA[i] = double.Parse(sMA[i]);
      }
      double oAR = AR.Length;
      double oMA = MA.Length;
      string[] resParams = sData[7].Split(';');
      double resMean = double.Parse(resParams[0]);
      double resStd = double.Parse(resParams[1]);
      ResidualDist dist = (resParams[0] == "N") ? ResidualDist.Normal : (resParams[0] == "T")?
ResidualDist.TDisr: (resParams[0] == "LN")? ResidualDist.LogNormal : ResidualDist.other;

      VARIMA[type][cluster].Add(new
ARIMA(AR,MA,double.Parse(sData[8]),sh,fh,type,cluster,dist,resMean,resStd,trans,mWeather,horizon));

    }
    static void Main(string[] args)
    {
      try
```

```
        {
            Thread.CurrentThread.CurrentCulture = new CultureInfo("en-US", false);
            string dName = "";
            if(!File.Exists("dirictory.dat"))
            {
                StreamWriter write = new StreamWriter("dirictory.dat");
                Console.WriteLine("Input working dirictory name");
                dName = Console.ReadLine();
                write.WriteLine(dName);
                write.Close();
            }
            else
            {
                StreamReader read = new StreamReader("dirictory.dat");
                dName = read.ReadLine();
                read.Close();
            }
            weatherModelling(dName);
        }
        catch (Exception e )
        {

            Console.WriteLine(e.Message);
            Console.WriteLine(e.Source);
            Console.WriteLine(e.StackTrace);
            Console.WriteLine("Press Enter to exit");
            Console.ReadLine();
        }
    }
}
```

Listing A-4. *VBA implementation of Haversine formula*

```
Function GetDistance(ByVal lat1 As Double, ByVal lon1 As Double, ByVal lat2 As Double, ByVal lon2 As
Double) As Double
Dim dLat, a, c As Double
dLat = (lat2 – lat1)
dLon = (lon2 – lon1)
a = Math.Sin(dLat * Factor / 2) * Math.Sin(dLat * Factor / 2) + Math.Sin(dLon * Factor / 2) * Math.Sin(dLon *
Factor / 2) * Math.Cos(lat1 * Factor) * Math.Cos(lat2 * Factor)
c = 2 * ArcTan2(Math.Sqr(a), Math.Sqr(1 – a))
GetDistance = R * c
End Function
```

Listing A-5. *VBA implementation of Bearing calculation formula*

```
Function Bearing(ByVal lat1 As Double, ByVal lon1 As Double, ByVal lat2 As Double, ByVal lon2 As
Double) As Double
Dim X As Double
Dim Y As Double
dLon = lon2 – lon1
Y = Math.Sin(dLon * Factor) * Math.Cos(lat2 * Factor)
X = Math.Cos(lat1 * Factor) * Math.Sin(lat2 * Factor) – Math.Sin(lat1 * Factor) * Math.Cos(lat2 * Factor) *
Math.Cos(dLon * Factor)
Bearing = ArcTan2(Y, X) / Factor + 360
Bearing = Bearing – (360 * Fix(Bearing / 360))
End Function
```

Listing A-6. *VBA implementation of formulas for calculation of destination's latitude and longtitude*

```
Function GetLat2(ByVal lat1 As Double, ByVal brng As Double, ByVal d As Double) As Double
GetLat2 = ASin(Math.Sin(lat1 * Factor) * Math.Cos(d / R) + Math.Cos(lat1 * Factor) * Math.Sin(d / R) *
Math.Cos(brng * Factor)) / Factor
End Function

Function GetLon2(ByVal lat1 As Double, ByVal lon1 As Double, ByVal lat2 As Double, ByVal d As Double,
ByVal brng As Double) As Double
GetLon2 = lon1 + (ArcTan2(Math.Sin(brng * Factor) * Math.Sin(d / R) * Math.Cos(lat1 * Factor), Math.Cos(d /
R) – Math.Sin(lat1 * Factor) * Math.Sin(lat2 * Factor))) / Factor
End Function
```

Listing A-7. *Getting latitude and longitude of a point from its 3d coordinates*

```
Function vToSpheric(ByVal ex As Double, ByVal ey As Double, ByVal ez As Double, f As Double, l As
Double) As Boolean
f = ArcTan2(ez, Sqr(ex * ex + ey * ey))
l = ArcTan2(-ey, ex)
End Function
```

Listing A-8. *Finding a unit perpendicular vector*

```
Function vOrt(ByVal lat1 As Double, ByVal lon1 As Double, ByVal lat2 As Double, ByVal lon2 As Double, x
As Double, y As Double, z As Double) As Boolean
a = vMult(lat1, lon1, lat2, lon2, x, y, z)
n = vLength(x, y, z)
If n <> 0 Then
x = x / n
y = y / n
z = z / n
End If
vOrt = True
End Function
```

Listing A-9. *Vector cross product of a pair of vectors*

```
Function vVMult(ByVal e1x As Double, ByVal e1y As Double, ByVal e1z As Double, ByVal e2x As Double,
ByVal e2y As Double, ByVal e2z As Double, x As Double, y As Double, z As Double) As Boolean
x = e1y * e2z – e2y * e1z
y = e1z * e2x – e2z * e1x
z = e1x * e2y – e1y * e2x
End Function
```

Listing A-10. *Robust function for calculation of vector cross product of a pair of vectors, defined in spherical coordinates*

```
Function vMult(ByVal lat1 As Double, ByVal lon1 As Double, ByVal lat2 As Double, ByVal lon2 As Double,
x As Double, y As Double, z As Double) As Boolean

 x = Sin(lat1 – lat2) * Sin((lon1 + lon2) / 2) * Cos((lon1 – lon2) / 2) – Sin(lat1 + lat2) * Cos((lon1 + lon2) / 2) *
Sin((lon1 – lon2) / 2)
 y = Sin(lat1 – lat2) * Cos((lon1 + lon2) / 2) * Cos((lon1 – lon2) / 2) + Sin(lat1 + lat2) * Sin((lon1 + lon2) / 2) *
Sin((lon1 – lon2) / 2)
 z = Cos(lat1) * Cos(lat2) * Sin(lon1 – lon2)
```

```
 MultVect = True

End Function
```

Listing A-11. *Calculation of the length of some vector, which begins in the center of the corresponding coordinates system.*

```
Function vLength(ByVal x As Double, ByVal y As Double, ByVal z As Double) As Double
vLength = Sqr(x * x + y * y + z * z)
End Function
```

Listing A-12. *VBA implementation of the formal algorithm for great circles intersection finding*

```
Function GetIntersection(ByVal lat11 As Double, ByVal lon11 As Double, ByVal lat12 As Double, ByVal
lon12 As Double, ByVal lat21 As Double, ByVal lon21 As Double, ByVal lat22 As Double, ByVal lon22 As
Double, f1 As Double, l1 As Double, f2 As Double, l2 As Double) As Boolean
Dim ax As Double
Dim ay As Double
Dim az As Double
Dim bx As Double
Dim by As Double
Dim bz As Double
Dim x As Double
Dim y As Double
Dim z As Double
a = vOrt(lat11 * Factor, -lon11 * Factor, lat12 * Factor, -lon12 * Factor, ax, ay, az)
b = vOrt(lat21 * Factor, -lon21 * Factor, lat22 * Factor, -lon22 * Factor, bx, by, bz)
c = vVMult(ax, ay, az, bx, by, bz, x, y, z)
d = vToSpheric(x, y, z, f1, l1)
f2 = -f1
l2 = l1 + PI
f1 = f1 / Factor
f2 = f2 / Factor
l1 = -l1 / Factor
l2 = -l2 / Factor
f1 = correctDir(f1)
f2 = correctDir(f2)
l1 = correctDir(l1)
l2 = correctDir(l2)
GetIntersection = True
End Function
```

Listing A-13. *Deleting model specific objects of the previous model and creating the group of blocks for the new one.*

```
    model.ActiveView.Selection.SelectAll
   model.Shapes(model.Shapes.Find(smFindTag, "object.9934")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.9940")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.9941")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.9950")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.9951")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.99511")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.99501")).Selected = False
   model.Shapes(model.Shapes.Find(smFindTag, "object.99411")).Selected = False
```

```
model.Shapes(model.Shapes.Find(smFindTag, "object.99401")).Selected = False
model.Shapes(model.Shapes.Find(smFindTag, "object.99341")).Selected = False
model.ActiveView.Selection.Delete
model.ActiveView.Selection.DeselectAll
Set crmod = model.Modules.Create("BasicProcess", "Create", -6000, 1500)
Set psmod = model.Modules.Create("AdvancedTransfer", "Route", -4500, 1500)
crmod.Data("Name") = "CreateVessels"
crmod.Data("Entity Type") = "Vessel"
crmod.Data("Interarrival Type") = "Constant"
crmod.Data("Units") = "Seconds"
crmod.Data("Batch Size") = "v_Vessels(1,1)"
crmod.Data("Max Batches") = "1"
crmod.UpdateShapes
psmod.Data("Name") = "LeaveCreate"
psmod.Data("Station") = "VBA_PROC"
psmod.Data("RouteTime") = "0"
psmod.Data("Units") = "Hours"
psmod.Data("SG") = "Station"
psmod.UpdateShapes
model.ActiveView.Selection.DeselectAll
```

Listing A-14. *Building installation-specific blocks*

```
model.ActiveView.Selection.DeselectAll
    Set stmod = model.Modules.Create("AdvancedTransfer", "Station", 0, i * 1000)
    stmod.Data("Name") = LineItems(0)
    stmod.Data("Station Type") = "Station"
    stmod.Data("Statn") = LineItems(0)
    stmod.UpdateShapes
    Set procmod = model.Modules.Create("BasicProcess", "Process", 1500, i * 1000)
    procmod.Data("ValueAdded") = "Value Added"
    procmod.Data("Units") = "Hours"
    procmod.Data("DelayType") = "Expression"
    If (LineItems(0) <> "FBS") Then
      procmod.Data("Action") = "Seize Delay"
      procmod.Data("Resource Type(1)") = "Resource"
      procmod.Data("Resource Name(1)") = "Crane" & LineItems(0)
      procmod.Data("Quantity(1)") = "1"
    Else
      procmod.Data("Action") = "Delay"
    End If
    procmod.Data("Expression") = "0"
    procmod.Data("Priority") = "Medium(2)"
    procmod.Data("Type") = "Standard"
    procmod.Data("Name") = "ServiceBegin" & LineItems(0)
    procmod.UpdateShapes
    Set psmod = model.Modules.Create("AdvancedTransfer", "Route", 3000, i * 1000)
    psmod.Data("Name") = "LeaveForService" & LineItems(0)
    psmod.Data("Station") = "VBA_SERVICE"
    psmod.Data("RouteTime") = "0"
    psmod.Data("Units") = "Hours"
    psmod.Data("SG") = "Station"
    psmod.UpdateShapes
    model.ActiveView.Selection.DeselectAll
    Set stmod = model.Modules.Create("AdvancedTransfer", "Station", 4500, i * 1000)
    stmod.Data("Name") = LineItems(0) & "_SERVICE"
    stmod.Data("Station Type") = "Station"
    stmod.Data("Statn") = LineItems(0) & "_SERVICE"
    stmod.UpdateShapes
    Set procmod = model.Modules.Create("BasicProcess", "Process", 6000, i * 1000)
```

```
    procmod.Data("ValueAdded") = "Value Added"
    procmod.Data("Units") = "Hours"
    procmod.Data("DelayType") = "Expression"
    If (LineItems(0) <> "FBS") Then
      procmod.Data("Action") = "Delay Release"
      procmod.Data("Resource Type(1)") = "Resource"
      procmod.Data("Resource Name(1)") = "Crane" & LineItems(0)
      procmod.Data("Quantity(1)") = "1"
    Else
      procmod.Data("Action") = "Delay"
    End If
    procmod.Data("Expression") = "v_Durations(Entity.SerialNumber,2)"
    procmod.Data("Priority") = "Medium(2)"
    procmod.Data("Type") = "Standard"
    procmod.Data("Name") = "ServiceEnd" & LineItems(0)
    procmod.UpdateShapes
    Set psmod = model.Modules.Create("AdvancedTransfer", "Route", 7500, i * 1000)
    psmod.Data("Name") = "Leave" & LineItems(0)
    psmod.Data("Station") = "VBA_PROC"
    psmod.Data("RouteTime") = "0"
    psmod.Data("Units") = "Hours"
    psmod.Data("SG") = "Station"
    psmod.UpdateShapes
model.ActiveView.Selection.DeselectAll
```

Listing A-15. *VBA script for sailing times between any pair of locations calculation, vessels' routing and a posteriori improvements*

```
Private Sub VBA_Block_40_Fire()
    Dim model As Arena.model
    Dim sim As Arena.SIMAN
    Dim api As Arena.Application
    Set sim = ThisDocument.model.SIMAN
    Set model = ThisDocument.model
    Set api = ThisDocument.model.Application
    Dim loc As Long
    loc = sim.ActiveEntity
    ID = sim.EntitySerialNumber(loc) - 1
    sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 1)) = 0
    sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 2)) = 0
    destId = v_sequence(ID, v_step(ID))

    v_visitcounter = v_visitcounter + 1
    TNOW = sim.TimeSinceLastClear()
    lastvisitID = v_lastvisit(ID)
    v_lastvisit(ID) = v_visitcounter - 1

    If lastvisitID <= UBound(v_results, 2) Then

        deltaDep = TNOW - v_results(curReplication - 1, lastvisitID, 6)


    End If

    destStation = v_bijection(destId)
    sim.VariableArrayValueAsVariant(sim.SymbolNumber("v_Visits", ID + 1, 1)) = destStation
    sim.VariableArrayValueAsVariant(sim.SymbolNumber("v_Visits", ID + 1, 2)) = destStation & "_service"
```

```
    T_S = 0
    W_T = 0
    If v_step(ID) > 0 And TNOW <> 0 Then 'sailing time calculation
        If v_step(ID) > 0 Then
            posID = v_sequence(ID, v_step(ID) - 1)
        Else
            posID = v_sequence(ID, v_steps(ID) - 1)
        End If
        totDist = GetDistance(v_posn(posID, 0), v_posn(posID, 1), v_posn(destId, 0), v_posn(destId, 1))
        Dim ptsCW() As Double
        GCI = GetClusterIntersections(v_posn(posID, 0), v_posn(posID, 1), v_posn(destId, 0), v_posn(destId, 1), ptsCW)
        curBear = Bearing(v_posn(posID, 0), v_posn(posID, 1), v_posn(destId, 0), v_posn(destId, 1))
        covDist = 0
        curDist = 0
        nextWDirClust = ReturnWindDirCluster(v_posn(posID, 0), v_posn(posID, 1))
        nextWHeightClust = ReturnWaveHeightCluster(v_posn(posID, 0), v_posn(posID, 1))
        dt = dto
        T_S = TNOW

        legSpeed = RecoverSpeed(ID) ' recovery of the original leg speed



        nextWheight = v_weather(Fix(T_S / 3), nextWHeightClust)
        nextWDirX = v_weather(Fix(T_S / 3), v_cluster(0) + nextWDirClust)
        nextWDirY = v_weather(Fix(T_S / 3), v_cluster(0) + v_cluster(1) + nextWDirClust)
        nextWDir = WaveDirection(nextWDirX, nextWDirY)

        ' improvement strategies 2, 3, 4 and 6
        If ((v_improv_type = 2 Or v_improv_type = 3 Or v_improv_type = 4 Or (v_improv_type = 6 And destStation <> "FBS")) And destStation <> "OFP") Then

            expSailingTime = totDist / RealSpeed(legSpeed, nextWheight, nextWDir, curBear, v_dweight(ID))
            If (nextWheight < 4.5 And v_servicing(destId) <> 0) Then
                expSericeTime = v_servicing(destId) * v_servicing(destId) / CurServTime(v_servicing(destId), nextWheight)
            ElseIf v_servicing(destId) <> 0 Then
                expSericeTime = v_servicing(destId) * v_servicing(destId) / CurServTime(v_servicing(destId), 4.49)
            Else
                expSericeTime = 0
            End If
            schedSailingTime = totDist / legSpeed

            If (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime + schedSailingTime > 0) Then

                If v_improv_type = 2 Or (v_improv_type = 6 And destStation <> "FBS") And (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime) <> 0 Then
                    legSpeed = totDist / (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime + schedSailingTime)
                ElseIf v_improv_type = 3 And (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime) < 0 Then
                    legSpeed = totDist / (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime + schedSailingTime)
                ElseIf v_improv_type = 4 And (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime) > 0 Then
                    legSpeed = totDist / (v_exptime(ID, v_step(ID), 2) - v_exptime(ID, v_step(ID) - 1, 2) - expSailingTime - expSericeTime + schedSailingTime)
```

```
                End If

            End If

        End If


        If (legSpeed < v_speed_base(ID, 1)) Then
            legSpeed = v_speed_base(ID, 1)
        ElseIf (legSpeed > v_speed_base(ID, 2)) Then
            legSpeed = v_speed_base(ID, 2)
        End If

        ' end improvement strategies 2, 3, 4 and 6

        curDist = 0
        dtc = 0
        dtl = 0
        dt = dto
        dtb = (Fix(T_S / 3) + 1) * 3 - T_S
        If dtb < dt Then
            dt = dtb
        Else
            dt = dto
        End If
        While covDist <= totDist


            curWDirClust = nextWDirClust
            curWHeightClust = nextWHeightClust
            curWheight = nextWheight
            curWDir = nextWDir
            EcurDist = RealSpeed(legSpeed, curWheight, curWDir, curBear, v_dweight(ID)) * dt
            EcovDist = covDist + EcurDist
            ElatD = GetLat2(v_posn(posID, 0), curBear, EcovDist)
            ElonD = GetLon2(v_posn(posID, 0), v_posn(posID, 1), ElatD, EcovDist, curBear)
            nextWDirClust = ReturnWindDirCluster(ElatD, ElonD)
            nextWHeightClust = ReturnWaveHeightCluster(ElatD, ElonD)
            curDist = 0
            dtc = 0
            While dtc < dt
                If (nextWDirClust <> curWDirClust Or nextWHeightClust <> curWHeightClust) And v_inter Then
                    curDist1 = 0
                    curDist2 = 0
                    dtl = 0
                    If nextWDirClust <> curWDirClust Then
                        If ptsCW(1, curWDirClust, nextWDirClust, 3) = 0 Then
                            curDist2 = ptsCW(1, curWDirClust, nextWDirClust, 2) - covDist
                        ElseIf Abs(ptsCW(1, curWDirClust, nextWDirClust, 0) - latD) + Abs(ptsCW(1, curWDirClust,
nextWDirClust, 1) - lonD) < Abs(ptsCW(1, curWDirClust, nextWDirClust, 3) - latD) + Abs(ptsCW(1,
curWDirClust, nextWDirClust, 4) - lonD) And ptsCW(1, curWDirClust, nextWDirClust, 2) >= covDist Then
                            curDist2 = ptsCW(1, curWDirClust, nextWDirClust, 2) - covDist
                        ElseIf ptsCW(1, curWDirClust, nextWDirClust, 5) >= covDist Then
                            curDist2 = ptsCW(1, curWDirClust, nextWDirClust, 5) - covDist
                        Else
                            curDist2 = 0
                            GoTo m
                        End If
                    End If
                    If nextWHeightClust <> curWHeightClust Then
```

```
                        If ptsCW(0, curWHeightClust, nextWHeightClust, 3) = 0 And ptsCW(0, curWHeightClust,
nextWHeightClust, 2) >= covDist Then
                            curDist1 = ptsCW(0, curWHeightClust, nextWHeightClust, 2) - covDist
                        ElseIf Abs(ptsCW(0, curWHeightClust, nextWHeightClust, 0) - latD) + Abs(ptsCW(0,
curWHeightClust, nextWHeightClust, 1) - lonD) < Abs(ptsCW(0, curWHeightClust, nextWHeightClust, 3) -
latD) + Abs(ptsCW(0, curWHeightClust, nextWHeightClust, 4) - lonD) And ptsCW(0, curWHeightClust,
nextWHeightClust, 2) >= covDist Then
                            curDist1 = ptsCW(0, curWHeightClust, nextWHeightClust, 2) - covDist
                        ElseIf ptsCW(0, curWHeightClust, nextWHeightClust, 5) >= covDist Then
                            curDist1 = ptsCW(0, curWHeightClust, nextWHeightClust, 5) - covDist
                        Else
                            curDist1 = 0
                            GoTo m
                        End If
                    End If
                    If curDist1 = 0 And curDist2 = 0 Then
                        GoTo m
                    End If
                    If curDist2 = 0 And curDist1 <> 0 Or (curDist1 < curDist2 And curDist1 <> 0) Then
                        curDist = curDist + curDist1
                        curSpeed = RealSpeed(legSpeed, curWheight, curWDir, curBear, v_dweight(ID))
                        dtc = dtc + curDist1 / curSpeed
                        curWHeightClust = nextWHeightClust
                        curWheight = v_weather((Fix((T_S + dtc) / 3)), curWHeightClust)
                        curSpeed = RealSpeed(legSpeed, curWheight, curWDir, curBear, v_dweight(ID))
                    ElseIf curDist1 = 0 And curDist2 <> 0 Or (curDist1 >= curDist2 And curDist2 <> 0) Then
                        curDist = curDist + curDist2
                        curWDirClust = nextWDirClust
                        curSpeed = RealSpeed(legSpeed, curWheight, curWDir, curBear, v_dweight(ID))
                        dtc = dtc + curDist2 / curSpeed
                        curWDirX = v_weather((Fix((T_S + dtc) / 3)), v_cluster(0) + curWDirClust)
                        curWDirY = v_weather((Fix((T_S + dtc) / 3)), v_cluster(0) + v_cluster(1) + curWDirClust)
                        curWDir = WaveDirection(curWDirX, curWDirY)
                        curSpeed = RealSpeed(legSpeed, curWheight, curWDir, curBear, v_dweight(ID))
                        If curDist1 = curDist2 Then
                            curWHeightClust = nextWHeightClust
                            curWheight = v_weather((Fix((T_S + dtc) / 3)), curWHeightClust)
                        End If
                    End If
                Else
m:
                    dtl = dt - dtc
                    curSpeed = RealSpeed(legSpeed, curWheight, curWDir, curBear, v_dweight(ID))
                    curDist3 = curSpeed * dtl
                    curDist = curDist + curDist3
                    dtc = dt
                End If
            Wend
            covDist = covDist + curDist
            latD = GetLat2(v_posn(posID, 0), curBear, covDist)
            lonD = GetLon2(v_posn(posID, 0), v_posn(posID, 1), latD, covDist, curBear)
            If dtc = 0 Then
                T_S = T_S + dt
            Else
                T_S = T_S + dtc
            End If
            dt = dto
            dtb = (Fix(T_S / 3) + 1) * 3 - T_S
            If dtb < dt Then
                dt = dtb
```

```
            Else
                dt = dto
            End If
            nextWDirClust = ReturnWindDirCluster(latD, lonD)
            nextWHeightClust = ReturnWaveHeightCluster(latD, lonD)
            nextWheight = v_weather((Fix(T_S / 3)), nextWHeightClust)
            nextWDirX = v_weather((Fix(T_S / 3)), v_cluster(0) + nextWDirClust)
            nextWDirY = v_weather((Fix(T_S / 3)), v_cluster(0) + v_cluster(1) + nextWDirClust)
            nextWDir = WaveDirection(nextWDirX, nextWDirY)
        Wend
        T_S = T_S - (covDist - totDist) / (curSpeed)
        latD = GetLat2(v_posn(posID, 0), curBear, totDist)
        lonD = GetLon2(v_posn(posID, 0), v_posn(posID, 1), latD, totDist, curBear)
        W_T = 0
    ElseIf TNOW = 0 Then 'beginning of a replication
        W_T = 0
        T_S = v_exptime(ID, v_step(ID), 2)
        S_T = 0
        latD = v_posn(destId, 0)
        lonD = v_posn(destId, 1)
        totDist = 0
        v_visited(destId) = v_visited(destId) + 1
        'destStation , v_vname(ID) , & vbCrLf
        wResW = WriteResults(curReplication - 1, v_visitcounter - 1, destId, ID, (v_exptime(ID, v_step(ID), 0) +
v_extratime(ID)), (v_exptime(ID, v_step(ID), 0) + v_extratime(ID)), (v_exptime(ID, v_step(ID), 1) +
v_extratime(ID)), (v_exptime(ID, v_step(ID), 1) + v_extratime(ID)), (v_exptime(ID, v_step(ID), 2) +
v_extratime(ID)), (v_exptime(ID, v_step(ID), 2) + v_extratime(ID)), v_visited(destId), latD, lonD, totDist, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0)
        'v_results(curReplication-1,v_visitcounter)
        sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 1)) = T_S
        sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 2)) = 0 ' add sercice time
        Exit Sub
    ElseIf v_step(ID) = 0 And TNOW <> 0 Then 'beginning of the next voyage
        W_T = 0
        T_S = TNOW
        latD = v_posn(destId, 0)
        lonD = v_posn(destId, 1)
        totDist = 0
        sTime = 0
        sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 1)) = 0
        sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 2)) = 0
        wResW = WriteResults(curReplication - 1, v_visitcounter - 1, destId, ID, T_S, (v_exptime(ID, v_step(ID),
0) + v_extratime(ID)), T_S, (v_exptime(ID, v_step(ID), 1) + v_extratime(ID)), T_S, (v_exptime(ID, v_step(ID),
2) + v_extratime(ID)), v_visited(destId), latD, lonD, totDist, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)

        Exit Sub
    End If
    'waiting for arrival at the base time and a posteriori improvements of type 1 are incorporated here
    If destStation = "FBS" And T_S < v_exptime(ID, v_step(ID), 0) And v_improv_type <> 1 Then
        W_T = v_exptime(ID, v_step(ID), 0) - T_S
        ' improvements 5 and 6 is incorporated here
        ids1 = -1
        idsStep1 = -1
        maxDev = -1
        If W_T > 0 And (v_improv_type = 5 Or v_improv_type = 6) And v_bijection(posID) <> "FBS" Then

            For ids = 0 To v_vessnum - 1

                If (ids <> ID) Then
```

```
        idsStep = v_step(ids)
        idsLast = idsStep - 1
        If (idsLast = -1) Then

            idsLast = v_steps(ids) + idsLast

        End If


        If (TNOW - v_exptime(ids, v_step(ids), 0) > 0) And v_sequence(ids, idsLast) <> 0 Then

            idsStep = v_step(ids)
            idsDest = v_sequence(ids, idsStep)
            idsStation = v_bijection(idsDest)
            While (idsDest <> 0)

                idsStep = idsStep + 1
                If (idsStep = v_steps(ids)) Then
                    idsStep = 0
                End If
                idsDest = v_sequence(ids, idsStep)
                idsStation = v_bijection(idsDest)

            Wend

            If v_exptime(ID, v_step(ID), 2) - v_exptime(ids, idsStep, 2) > maxDev Then

                ids1 = ids
                idsStep1 = idsStep
                maxDev = v_exptime(ID, v_step(ID), 2) - v_exptime(ids, idsStep, 2)

            End If

        End If

    End If

Next ids

If (maxDev <> -1) Then

    'MsgBox (curReplication & "  " & v_visitcounter)

    ids = ids1
    If (idsStep1 = v_steps(ids)) Then
        idsStep1 = 0
    End If
    idStep1 = v_step(ID)
    If (idStep1 = v_steps(ID)) Then
        idStep1 = 0
    End If
    idStep0 = v_step(ID)
    idsStep0 = v_step(ids)
    idSteps0 = v_steps(ID)
    idsSteps0 = v_steps(ids)
    v_steps(ID) = (idsSteps0 - idsStep1) - (idSteps0 - idStep1) + idSteps0
    v_steps(ids) = -(idsSteps0 - idsStep1) + (idSteps0 - idStep1) + idsSteps0
    maxDim = CInt(MaxDoubl(v_steps(ID) - 1, v_steps(ids) - 1))
    maxDim = CInt(MaxDoubl(maxDim, UBound(v_sequence, 2)))
```

```
                If maxDim > UBound(v_sequence, 2) Then
                    ReDim Preserve v_sequence(v_vessnum, maxDim)
                End If
                'ReDim v_exptime(n - 1, m - 1, 2) As Double
                'ReDim v_legtime(n - 1, m - 1) As Double
                ReDim bufArr(maxDim, 4) As Double
                i2 = 0
                For i1 = 0 To v_steps(ID) - 1

                    bufArr(i1, 0) = v_sequence(ID, i1)
                    bufArr(i1, 1) = v_exptime(ID, i1, 0)
                    bufArr(i1, 2) = v_exptime(ID, i1, 1)
                    bufArr(i1, 3) = v_exptime(ID, i1, 2)
                    bufArr(i1, 4) = v_legtime(ID, i1)
                    If (i1 >= idStep1) Then

                        v_sequence(ID, i1) = v_sequence(ids, idsStep1 + i2)
                        v_exptime(ID, i1, 0) = v_exptime(ids, idsStep1 + i2, 0)
                        v_exptime(ID, i1, 1) = v_exptime(ids, idsStep1 + i2, 1)
                        v_exptime(ID, i1, 2) = v_exptime(ids, idsStep1 + i2, 2)
                        v_legtime(ID, i1) = v_legtime(ids, idsStep1 + i2)
                        i2 = i2 + 1

                    End If

                Next i1

                i2 = 0
                For i1 = 0 To v_steps(ids) - 1

                    If (i1 >= idsStep1) Then
                        If (idStep1 + i2 < v_steps(ID)) Then
                            v_sequence(ids, i1) = CInt(bufArr(idStep1 + i2, 0))
                            v_exptime(ids, i1, 0) = bufArr(idStep1 + i2, 1)
                            v_exptime(ids, i1, 1) = bufArr(idStep1 + i2, 2)
                            v_exptime(ids, i1, 2) = bufArr(idStep1 + i2, 3)
                            v_legtime(ids, i1) = bufArr(idStep1 + i2, 4)
                        Else
                            v_sequence(ids, i1) = v_sequence(ID, idStep1 + i2)
                            v_exptime(ids, i1, 0) = v_exptime(ID, idStep1 + i2, 0)
                            v_exptime(ids, i1, 1) = v_exptime(ID, idStep1 + i2, 1)
                            v_exptime(ids, i1, 2) = v_exptime(ID, idStep1 + i2, 2)
                            v_legtime(ids, i1) = v_legtime(ID, idStep1 + i2)
                        End If
                        i2 = i2 + 1

                    End If

                Next i1

            End If

        End If
        ' end improvements 5 and 6
    End If
    ' end improvement 1
    sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 1)) = T_S - TNOW + W_T ' sailing time statement

    ' write modelled parameters
```

```
    sailing_cost = (T_S - TNOW) * v_costs(ID, 1) * legSpeed * legSpeed * legSpeed / (v_speed_base(ID, 0) *
v_speed_base(ID, 0) * v_speed_base(ID, 0))

     If (v_step(ID) <> 0) Then
        If (destStation <> "OFP") Then
            wResW = WriteResults(curReplication - 1, v_visitcounter - 1, destId, ID, T_S, (v_exptime(ID,
v_step(ID), 0) + v_extratime(ID)), 0, (v_exptime(ID, v_step(ID), 1) + v_extratime(ID)), 0, (v_exptime(ID,
v_step(ID), 2) + v_extratime(ID)), 0, latD, lonD, totDist, (T_S - TNOW), W_T, 0, 0, v_servicing(destId),
sailing_cost, 0, 0, 0, 0)
        Else
            wResW = WriteResults(curReplication - 1, v_visitcounter - 1, destId, ID, T_S + W_T, T_S + W_T, T_S
+ W_T, T_S + W_T, T_S + W_T, T_S + W_T, v_visited(destId), latD, lonD, totDist, (T_S - TNOW), W_T, 0,
0, 0, sailing_cost, 0, 0, sailing_cost, sailing_cost * v_costs(ID, 0))
        End If
    End If
End Sub
```

Listing A-16. *VBA function for real speed with respect to WD and SWH calculation*

```
Function RealSpeed(ByVal ESpeed As Double, ByVal WHeight As Double, ByVal WDir As Double, ByVal
Bearing As Double, ByVal DWeight As Double)
Dim Q As Double
If WDir >= Bearing Then
Q = Bearing – WDir
Else
Q = 360 + WDir – Bearing
End If
If Q > 180 Then
Q = 360 – Q
End If
Q = Q * Factor
RealSpeed = (ESpeed/1.852 – WHeight * (0.745 + 0.245 * Q) * (1# – 0.00000135 * DWeight *
ESpeed/1.852))*1.852
End Function
```

Listing A-17. *VBA script for servicing times at any location calculation*

```
Private Sub VBA_Block_41_Fire() ' servicing of a vessel and releasing the resource
    Dim model As Arena.model
    Dim sim As Arena.SIMAN
    Dim api As Arena.Application
    Set sim = ThisDocument.model.SIMAN
    Set model = ThisDocument.model
    Set api = ThisDocument.model.Application
    Dim loc As Long
    loc = sim.ActiveEntity
    ID = sim.EntitySerialNumber(loc) - 1
    sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 1)) = 0
    sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 2)) = 0
    posID = v_sequence(ID, v_step(ID))
    posStation = v_bijection(posID)

    TNOW = sim.TimeSinceLastClear()
    lastvisitID = v_lastvisit(ID)
    dHour = TNOW - Fix((TNOW) / 24) * 24 'hour of the day
    If TNOW = 0 Or (v_step(ID) = 0) Then


        v_step(ID) = v_step(ID) + 1
```

```
        If v_step(ID) >= v_steps(ID) Then
            v_step(ID) = 0
        End If
        Exit Sub

    End If
    'servicing begins
    wTime = 0
    If (dHour < v_twindows(posID, 0) Or dHour > v_twindows(posID, 1)) Then
        If (dHour < v_twindows(posID, 0)) Then
            wTime = v_twindows(posID, 0) - dHour
        ElseIf dHour > v_twindows(posID, 1) Then
            wTime = 24 - dHour + v_twindows(posID, 0)
        End If
    End If
    If (TNOW + wTime) < v_exptime(ID, v_step(ID), 1) And posStation = "FBS" And v_improv_type <> 1 Then
' improvement of typr 1 additional notes
        wTime = wTime + v_exptime(ID, v_step(ID), 1) - (TNOW + wTime)
    End If
    dt = Fix((wTime + TNOW) / 3) * 3 + 3 - (wTime + TNOW)
    sTime = 0
    tTime = 0
    cTime = 0
    curWHeightClust = ReturnWaveHeightCluster(v_posn(posID, 0), v_posn(posID, 1))
    If (posStation <> "OFP") Then
        While tTime <= v_servicing(posID)
            dHour = TNOW + wTime + sTime - Fix((TNOW + wTime + sTime) / 24) * 24
            If (dHour < v_twindows(posID, 0) Or dHour > v_twindows(posID, 1)) Then
                If (dHour < v_twindows(posID, 0)) Then
                    wTime = wTime + v_twindows(posID, 0) - dHour
                ElseIf dHour > v_twindows(posID, 1) Then
                    wTime = wTime + 24 - dHour + v_twindows(posID, 0)
                End If
            End If

            If posStation <> "FBS" Then
                cTime = CurServTime(dt, curWheight)
            Else

                cTime = CurServTime(dt, curWheight)

            End If

            tTime = tTime + cTime
            sTime = sTime + dt

            curWheight = v_weather((Fix((TNOW + wTime + sTime) / 3)), curWHeightClust)
            dt = 3
        Wend
        If tTime > v_servicing(posID) Then
            sTime = sTime - (tTime - v_servicing(posID)) * dt / cTime
        End If
    ElseIf posStation = "OFP" Then

        sTime = v_servicing(posID)

    End If
    ' servicing ends
    sim.VariableArrayValue(sim.SymbolNumber("v_Durations", ID + 1, 2)) = sTime + wTime
```

```
  If (posStation = "FBS") Then
    base_cost = (sTime + wTime) * v_costs(ID, 2)
    inst_cost = 0
  Else
    base_cost = 0
    inst_cost = (sTime + wTime) * v_costs(ID, 3)
  End If
  v_visited(posID) = v_visited(posID) + 1
  v_results(curReplication - 1, lastvisitID, 4) = TNOW + wTime
  v_results(curReplication - 1, lastvisitID, 6) = TNOW + wTime + sTime
  v_results(curReplication - 1, lastvisitID, 8) = v_visited(posID)
  v_results(curReplication - 1, lastvisitID, 13) = TNOW - v_results(curReplication - 1, lastvisitID, 2)
  v_results(curReplication - 1, lastvisitID, 14) = wTime
  v_results(curReplication - 1, lastvisitID, 15) = sTime
  v_results(curReplication - 1, lastvisitID, 18) = base_cost
  v_results(curReplication - 1, lastvisitID, 19) = inst_cost
  v_results(curReplication - 1, lastvisitID, 20) = base_cost + inst_cost + v_results(curReplication - 1,
lastvisitID, 17)
  v_results(curReplication - 1, lastvisitID, 21) = v_results(curReplication - 1, lastvisitID, 20) * v_costs(ID, 0)
  v_step(ID) = v_step(ID) + 1
  If v_step(ID) >= v_steps(ID) Then
    v_step(ID) = 0
    extraTime = v_exptime(ID, v_steps(ID) - 1, 2) - v_exptime(ID, 0, 2)
    v_extratime(ID) = v_extratime(ID) + extraTime
  End If
End Sub
```

Listing A-18. *VBA function for current utilized service time with respect to SWH calculation*

```
Function CurServTime(ByVal dt As Double, ByVal curWheight As Double) As Double
If curWheight < 2.5 Then
  CurServTime = dt
ElseIf curWheight >= 2.5 And curWheight < 3.5 Then
  CurServTime = dt / 1.2
ElseIf curWheight >= 3.5 And curWheight < 4.5 Then
  CurServTime = dt / 1.3
ElseIf curWheight >= 4.5 Then
  CurServTime = 0
End If
End Function
```

Listing A-19. *Call of an external *.exe file from VBA block*

```
Private Sub ModelLogic_RunEndSimulation()

  Dim wsh As Object
  Set wsh = VBA.CreateObject("WScript.Shell")
  Dim waitOnReturn As Boolean: waitOnReturn = True
  Dim windowStyle As Integer: windowStyle = 1
  Dim errorCode As Integer
  obj = wsh.Run("analize.exe", windowStyle, waitOnReturn)

End Sub
```

Listing A-20. *C# code for analyze.exe*

```
using System;
```

```
using System.Collections.Generic;
using System.IO;
using System.Linq;
using System.Text;
namespace Batching_Meaning
{
    class Program
    {
        public class Pair<T, U>
        {
            public Pair()
            {
            }
            public Pair(T first, U second)
            {
                this.First = first;
                this.Second = second;
            }
            public T First { get; set; }
            public U Second { get; set; }
        };
        static void Main(string[] args)
        {
            try
            {

                StreamReader read = new StreamReader(@"params.csv");
                read.ReadLine();
                string[] param = read.ReadLine().Split(';');
                int serv = 0;
                double[] curTime = new double[3];
                double[] curSched = new double[3];
                double h = double.Parse(param[0]);
                double z_quont = 1.960;
                double t_quont = 1.960;
                int k = int.Parse(param[1]);
                int lines = 0;
                int m = int.Parse(param[2]);
                int vv = 0;
                int vvv = 0;
                int i = 0;
                int j = 0;
                int v = 0;
                Dictionary<string,Pair <int,List<double>>> voyParams = new Dictionary<string, Pair<int,
List<double>>>();
                Console.WriteLine("k = " + k + " m = " + m + " h = " + h);
                Dictionary<string, int> visits = new Dictionary<string, int>();
                read.ReadLine();
                while (!read.EndOfStream)
                {
                    param = read.ReadLine().Split(';');
                    visits.Add(param[0], int.Parse(param[1]));
                }
                read.Close();
                double [,,] arrTimes = new double[k,m,2];
                double[, ,] dispTimes = new double[k, m, 2];
                double[, ,] depTimes = new double[k, m, 2];
                double[,] fcCosts = new double[k,5];
                double [,] avrSched = new double[k,2];
                List<Pair<double,double>> avrVoy = new List<Pair<double, double>>();
```

```
                double [] avrCosts = new double[5];
                double [] stdCosts = new double[5];
                double [] avrParams = new double[14];
                double [] stdParams = new double[14];
                fcCosts.Initialize();
                stdCosts.Initialize();
                avrCosts.Initialize();
                arrTimes.Initialize();
                avrParams.Initialize();
                stdParams.Initialize();

                read = new StreamReader(@"output.csv");
                while (!read.EndOfStream)
                {

                    lines++;
                    string str = read.ReadLine();
                    if(str == "")
                        continue;
                    if (str[0] == 'L')
                        continue;
                    string[] line = str.Split(';');
                    if (!voyParams.ContainsKey(line[1]))
                    {
                        voyParams.Add(line[1],new Pair<int, List<double>>(0,new List<double>()));
                    }
                    curTime[0] = double.Parse(line[2]);
                    curSched[0] = double.Parse(line[3]);
                    if (curTime[0] == -1.0)
                    {

                        i++; // new replication begins
                        j = 0;
                        if(v>vv)
                          vv = v;
                        vvv += v;
                        //Console.WriteLine(v);
                        v = 0;
                        continue;
                    }
                    curTime[1] = double.Parse(line[4]);
                    curSched[1] = double.Parse(line[5]);
                    curTime[2] = double.Parse(line[6]);
                    curSched[2] = double.Parse(line[7]);
                    if (visits[line[0]] < (int)double.Parse(line[8]) || (j > 1 && double.Parse(line[12]) == 0) ||
(int)double.Parse(line[8])==0)
                    {
                        continue; // if the visit is not from the current schedule do not consider it
                    }
                    voyParams[line[1]].First++;
                    voyParams[line[1]].Second.Add(curTime[1]);

                    for (int y = 0; y < 5; y++)
                    {
                        fcCosts[i, y] += double.Parse(line[17 + y]);
                        avrCosts[y] += fcCosts[i, y];
                    }


                    double [] t = curTime;
```

```
double [] p = curSched;
double[] tard = new double[3];
double[] dev = new double[3];
for(int ii = 0;ii<3;ii++)
{
   if (line[0] != "OFP")
   {
      tard[ii] = Math.Max(t[ii] - p[ii], 0);
      dev[ii] = Math.Abs(t[ii] - p[ii]);
   }
   else
   {
      tard[ii] = 0;
      dev[ii] = 0;
   }
}
try
{
   arrTimes[i, j, 0] = tard[0];
   arrTimes[i, j, 1] = dev[0];
   dispTimes[i, j, 0] = tard[1];
   dispTimes[i, j, 1] = dev[1];
   depTimes[i, j, 0] = tard[2];
   depTimes[i, j, 1] = dev[2];
}
catch(Exception e)
{
   Console.WriteLine(i + "  " + j);
   Console.WriteLine(str);

   continue;

}
avrParams[0] += (h - t[0] >= 0) ? 1 : 0;
if (line[0] == "FBS" && double.Parse(line[12])!=0)
{
   avrParams[3] += (p[1] - t[0] >= 0) ? 1 : 0;
   avrParams[6] += Math.Max(t[0] - p[0], 0);
   avrParams[7] += Math.Abs(p[0] - t[0]);
   avrVoy.Add(new Pair<double, double>(Math.Max(t[0] - p[0], 0), Math.Abs(p[0] - t[0])));
   int svv = 0;
   foreach (double voyParam in voyParams[line[1]].Second)
   {
      if (voyParam <= p[1])
         svv++;
   }
   avrParams[1] += ((double)svv) / (k * voyParams[line[1]].First);
   v++;
   if (visits[line[0]] == (int)double.Parse(line[8]) && (j + 1) == m)
   {
      avrParams[2] +=  ( p[1] - t[0] >= 0) ? 1 : 0;
      avrParams[4] += Math.Max(t[0] - p[0], 0);
      avrParams[5] += Math.Abs(p[0] - t[0]);
      avrSched[i, 0] =  Math.Max(t[0] - p[0], 0);
      avrSched[i, 1] =  Math.Abs(p[0] - t[0]);
   }

}
for (int ii = 0; ii < 3; ii++)
{
```

```
                    avrParams[8+2*ii] += tard[ii];
                    avrParams[8+2*ii+1] += dev[ii];
                }

                j++;

            }
            read.Close();

            for (int jj = 0; jj < 5; jj++)
            {
                avrCosts[jj] /= k;
                for (int ii = 0; ii < k; ii++)
                {
                    stdCosts[jj] += Math.Pow(fcCosts[ii, jj]-avrCosts[jj],2);
                }
                stdCosts[jj] = Math.Sqrt(stdCosts[jj])/(k-1);
            }

            Console.WriteLine(lines);
            Console.WriteLine(serv);
            Console.WriteLine(avrParams[0]);
            Console.WriteLine(avrParams[6]);
            Console.WriteLine(avrParams[7]);
            Console.WriteLine(vv);
            Console.WriteLine(vvv);
            v = vv;
            TextWriter write = new StreamWriter(@"keyfactors.csv");
            write.Write("E{SS};s{SS};ME{SS};LCI{SS}-95%;UCI{SS}-95%\t\n");
            avrParams[0] = avrParams[0]/(k*m);
            stdParams[0] = Math.Sqrt(avrParams[0] * (1 - avrParams[0])) / Math.Sqrt(k * m);
            double mESS = z_quont*stdParams[0]/Math.Sqrt(k*m);
            write.Write(avrParams[0] + ";" + stdParams[0] + ";" + mESS + ";" + (avrParams[0] - mESS) + ";" +
(avrParams[0] + mESS) + "\t\n");
            write.Write("E{SV};s{SV};ME{SV};LCI{SV}-95%;UCI{SV}-95%\t\n");
            avrParams[1] = avrParams[1] / (v);
            stdParams[1] = Math.Sqrt(avrParams[1] * (1 - avrParams[1])) / Math.Sqrt(k * v);
            mESS = z_quont * stdParams[1] / Math.Sqrt(k * v);
            write.Write(avrParams[1] + ";" + stdParams[1] + ";" + mESS + ";" + (avrParams[1] - mESS) + ";" +
(avrParams[1] + mESS) + "\t\n");
            write.Write("E{PS};s{PS};ME{PS};LCI{PS}-95%;UCI{PS}-95%\t\n");
            avrParams[2] = avrParams[2] / (k);
            stdParams[2] = Math.Sqrt(avrParams[2] * (1 - avrParams[2])) / Math.Sqrt(k);
            mESS = z_quont * stdParams[2] / Math.Sqrt(k);
            write.Write(avrParams[2] + ";" + stdParams[2] + ";" + mESS + ";" + (avrParams[2] - mESS) + ";" +
(avrParams[2] + mESS) + "\t\n");
            write.Write("E{PV};s{PV};ME{PV};LCI{SV}-95%;UCI{PV}-95%\t\n");
            avrParams[3] = avrParams[3] / (k*v);
            stdParams[3] = Math.Sqrt(avrParams[3] * (1 - avrParams[3])) / Math.Sqrt(k * v);
            mESS = z_quont * stdParams[3] / Math.Sqrt(k * v);
            write.Write(avrParams[3] + ";" + stdParams[3] + ";" + mESS + ";" + (avrParams[3] - mESS) + ";" +
(avrParams[3] + mESS) + "\t\n");
            avrParams[4] /= k;
            avrParams[5] /= k;
            avrParams[6] /= (k*v);
            avrParams[7] /= (k*v);
            for (int ii = 0; ii < 3; ii++)
            {
                avrParams[8 + 2*ii] = avrParams[8 + 2*ii]/(k*(m-visits["OFP"]));
                avrParams[8 + 2 * ii + 1] = avrParams[8 + 2 * ii + 1] / (k * (m - visits["OFP"]));
```

```
            }

            double[] metDev = new double[14];
            double[,] avrVoyR = new double[v,2];
            avrVoyR.Initialize();
            for (i = 0; i < k; i++)
            {
               stdParams[4] += Math.Pow(avrSched[i, 0] - avrParams[4], 2);
               stdParams[5] += Math.Pow(avrSched[i, 1] - avrParams[5], 2);
               for (j = 0; j < v; j++)
               {
                  try
                  {
                     avrVoyR[j, 0] = avrVoy[i*v + j].First/v;
                     avrVoyR[j, 1] = avrVoy[i*v + j].Second/v;
                  }
                  catch(Exception a)
                  {
                     avrVoyR[j, 0] = 0;
                     avrVoyR[j, 1] = 0;
                  }
               }
            }

            stdParams[5] = Math.Sqrt(stdParams[5])/(k - 1);
            stdParams[4] = Math.Sqrt(stdParams[4])/(k - 1);
            metDev[5] = t_quont * stdParams[5] / Math.Sqrt(k);
            metDev[4] = t_quont * stdParams[4] / Math.Sqrt(k);
            write.Write("E{TSs};s{TSs};ME{TSs};LCI{TSs}-95%;UCI{TSs}-95%\t\n");
            write.Write(avrParams[4] + ";" + stdParams[4] + ";" + metDev[4] + ";" + (avrParams[4] - metDev[4])
+ ";" + (avrParams[4] + metDev[4]) + "\t\n");
            write.Write("E{DSs};s{DSs};ME{DSs};LCI{DSs}-95%;UCI{DSs}-95%\t\n");
            write.Write(avrParams[5] + ";" + stdParams[5] + ";" + metDev[5] + ";" + (avrParams[5] - metDev[5])
+ ";" + (avrParams[5] + metDev[5]) + "\t\n");
            for (j = 0; j < v; j++)
            {
               stdParams[7] += Math.Pow(avrVoyR[j, 1] - avrParams[7], 2);
               stdParams[6] += Math.Pow(avrVoyR[j, 0] - avrParams[6], 2);
            }
            stdParams[7] = Math.Sqrt(stdParams[7]) / (v - 1);
            stdParams[6] = Math.Sqrt(stdParams[6]) / (v - 1);
            metDev[7] = t_quont * stdParams[7] / Math.Sqrt(v);
            metDev[6] = t_quont * stdParams[6] / Math.Sqrt(v);
            write.Write("E{TVs};s{TVs};ME{TVs};LCI{TVs}-95%;UCI{TVs}-95%\t\n");
            write.Write(avrParams[6] + ";" + stdParams[6] + ";" + metDev[6] + ";" + (avrParams[6] - metDev[6])
+ ";" + (avrParams[6] + metDev[6]) + "\t\n");
            write.Write("E{DVs};s{DVs};ME{DVs};LCI{DVs}-95%;UCI{DVs}-95%\t\n");
            write.Write(avrParams[7] + ";" + stdParams[7] + ";" + metDev[7] + ";" + (avrParams[7] - metDev[7])
+ ";" + (avrParams[7] + metDev[7]) + "\t\n");
            for (j = 0; j < m; j++ )
            {
               double [] avrTard = new double[3];
               double [] avrDev =  new double[3];
               for(i = 0; i < k; i++)
               {
                  avrTard[0] += arrTimes[i, j, 0];
                  avrDev[0] += arrTimes[i, j, 1];
                  avrTard[1] += dispTimes[i, j, 0];
                  avrDev[1] += dispTimes[i, j, 1];
                  avrTard[2] += depTimes[i, j, 0];
```

```
                        avrDev[2] += depTimes[i, j, 1];
                    }


                    for (int ii = 0; ii < 3; ii++)
                    {
                        stdParams[8 + 2 * ii] += Math.Pow(avrParams[8 + 2 * ii] - avrTard[ii] / k, 2);
                        stdParams[8 + 2 * ii + 1] += Math.Pow(avrParams[8 + 2 * ii + 1] - avrDev[ii] / k, 2);
                    }


                }

                for (int ii = 0; ii < 3; ii++)
                {
                    stdParams[8 + 2 * ii] = Math.Sqrt(stdParams[8 + 2 * ii] / (m - visits["OFP"] - 1));
                    stdParams[8 + 2 * ii + 1] = Math.Sqrt(stdParams[8 + 2 * ii + 1] / (m - visits["OFP"] -1));
                    metDev[8 + 2 * ii] = t_quont * stdParams[8 + 2 * ii] / Math.Sqrt(m- visits["OFP"] );
                    metDev[8 + 2 * ii + 1] = t_quont * stdParams[8 + 2 * ii + 1] / Math.Sqrt(m- visits["OFP"] );

                }
                write.Write("E{Ta};s{Ta};ME{Ta};LCI{Ta}-95%;UCI{Ta}-95%\t\n");
                write.Write(avrParams[7+1] + ";" + stdParams[7+1] + ";" + metDev[7+1] + ";" + (avrParams[7+1] -
metDev[7+1]) + ";" + (avrParams[7+1] + metDev[7+1]) + "\t\n");
                write.Write("E{Da};s{Da};ME{Da};LCI{Da}-95%;UCI{Da}-95%\t\n");
                write.Write(avrParams[8+1] + ";" + stdParams[8+1] + ";" + metDev[8+1] + ";" + (avrParams[8+1] -
metDev[8+1]) + ";" + (avrParams[8+1] + metDev[8+1]) + "\t\n");
                write.Write("E{Ts};s{Ts};ME{Ts};LCI{Ts}-95%;UCI{Ts}-95%\t\n");
                write.Write(avrParams[9+1] + ";" + stdParams[9+1] + ";" + metDev[9+1] + ";" + (avrParams[9+1] -
metDev[9+1]) + ";" + (avrParams[9+1] + metDev[9+1]) + "\t\n");
                write.Write("E{Ds};s{Ds};ME{Ds};LCI{Ds}-95%;UCI{Ds}-95%\t\n");
                write.Write(avrParams[10+1] + ";" + stdParams[10+1] + ";" + metDev[10+1] + ";" +
(avrParams[10+1] - metDev[10+1]) + ";" + (avrParams[10+1] + metDev[10+1]) + "\t\n");
                write.Write("E{Td};s{Td};ME{Td};LCI{Td}-95%;UCI{Td}-95%\t\n");
                write.Write(avrParams[11+1] + ";" + stdParams[11+1] + ";" + metDev[11+1] + ";" +
(avrParams[11+1] - metDev[11+1]) + ";" + (avrParams[11+1] + metDev[11+1]) + "\t\n");
                write.Write("E{Dd};s{Dd};ME{Dd};LCI{Dd}-95%;UCI{Dd}-95%\t\n");
                write.Write(avrParams[12+1] + ";" + stdParams[12+1] + ";" + metDev[12+1] + ";" +
(avrParams[12+1] - metDev[12+1]) + ";" + (avrParams[12+1] + metDev[12+1]) + "\t\n");

                write.Write("E{Sfc};s{Sfc};ME{Sfc};LCI{Sfc}-95%;UCI{Sfc}-95%\t\n");
                write.Write(avrCosts[0] + ";" + stdCosts[0] + ";" + z_quont * stdCosts[0] / Math.Sqrt(k) + ";" +
(avrCosts[0] - z_quont * stdCosts[0] / Math.Sqrt(k)) + ";" + (avrCosts[0] + z_quont * stdCosts[0] /
Math.Sqrt(k)) + "\t\n");
                write.Write("E{Bfc};s{Bfc};ME{Bfc};LCI{Bfc}-95%;UCI{Bfc}-95%\t\n");
                write.Write(avrCosts[1] + ";" + stdCosts[1] + ";" + z_quont * stdCosts[1] / Math.Sqrt(k) + ";" +
(avrCosts[1] - z_quont * stdCosts[1] / Math.Sqrt(k)) + ";" + (avrCosts[1] + z_quont * stdCosts[1] /
Math.Sqrt(k)) + "\t\n");
                write.Write("E{Ifc};s{Ifc};ME{Ifc};LCI{Ifc}-95%;UCI{Ifc}-95%\t\n");
                write.Write(avrCosts[2] + ";" + stdCosts[2] + ";" + z_quont * stdCosts[2] / Math.Sqrt(k) + ";" +
(avrCosts[2] - z_quont * stdCosts[2] / Math.Sqrt(k)) + ";" + (avrCosts[2] + z_quont * stdCosts[2] /
Math.Sqrt(k)) + "\t\n");
                write.Write("E{Tfc};s{Tfc};ME{Tfc};LCI{Tfc}-95%;UCI{Tfc}-95%\t\n");
                write.Write(avrCosts[3] + ";" + stdCosts[3] + ";" + z_quont * stdCosts[3] / Math.Sqrt(k) + ";" +
(avrCosts[3] - z_quont * stdCosts[3] / Math.Sqrt(k)) + ";" + (avrCosts[3] + z_quont * stdCosts[3] /
Math.Sqrt(k)) + "\t\n");
                write.Write("E{TCf};s{TCf};ME{TCf};LCI{TCf}-95%;UCI{TCf}-95%\t\n");
                write.Write(avrCosts[4] + ";" + stdCosts[4] + ";" + z_quont * stdCosts[4] / Math.Sqrt(k) + ";" +
(avrCosts[4] - z_quont * stdCosts[4] / Math.Sqrt(k)) + ";" + (avrCosts[4] + z_quont * stdCosts[4] /
Math.Sqrt(k)) + "\t\n");
```

```
                write.Close();
            }
            catch(Exception e)
            {
                Console.WriteLine(e.Message);
                Console.WriteLine(e.StackTrace);
                Console.WriteLine("Something Went Wrong. Most Likely You have the analysis files open in excel.
Try to close them and rerun again");
                Console.Read();
            }
        }
    }
}
```

Listing A-21. *C# code for TOPSIS*

```
Dictionary<string, double> Altern = new Dictionary<string, double>();
string[] names;
int n;
int m;
double[,] w;
double[,] X;
double[,] V;
double[,] A;
double[,] S;
StreamReader read = new StreamReader("TOPSIS_INPUT.csv");
read.ReadLine();
string[] line = read.ReadLine().Split(';');
n = int.Parse(line[0]);
m = int.Parse(line[1]);
read.ReadLine();
w = new double[n,2];
X = new double[m,n];
V = new double[m,n];
A = new double[n,2];
S = new double[m,2];
names = new string[m];

for (int k = 0; k < 2; k++)
{
    line = read.ReadLine().Split(';');
    for (int i = 0; i < n; i++)
    {
        w[i, k] = double.Parse(line[i]);
    }
}
read.ReadLine();
for (int i = 0; i < m; i++)
{
    line = read.ReadLine().Split(';');
    Altern.Add(line[0], 0);
    names[i] = line[0];
    for (int j = 0; j < n; j++)
    {
        X[i, j] = double.Parse(line[j + 1]);
    }
}
read.Close();
for (int j = 0; j < n; j++)
{
```

```
   for (int i = 0; i < m; i++)
   {
      double normS = 0;
      for (int k = 0; k < m; k++)
      {
         normS += X[k, j]*X[k, j];
      }
      normS = Math.Sqrt(normS);
      V[i, j] = X[i, j]*w[j, 0]/normS;
   }
}
for (int k = 0; k < 2; k++)
{
   for (int j = 0; j < n; j++)
   {
      double mult = (k == 0) ? 1 : -1;
      mult *= w[j, 1];
      double max = double.MinValue;
      for (int i = 0; i < m; i++)
      {
         if (V[i, j]*mult > max)
         {
            max = V[i, j]*mult;
         }
      }
      A[j, k] = max*mult;
   }
}
for (int k = 0; k < 2; k++)
{
   for (int i = 0; i < m; i++)
   {
      S[i, k] = 0;
      for (int j = 0; j < n; j++)
      {
         S[i, k] += Math.Pow(V[i, j] – A[j, k], 2);
      }
      S[i, k] = Math.Sqrt(S[i, k]);
      if (k == 1)
         Altern[names[i]] = S[i, 0]/(S[i, 0] + S[i, 1]);
   }
}
StreamWriter write = new StreamWriter("TOPSIS_OUTPUT.csv");
write.WriteLine("Alternative;RC value");
List<KeyValuePair<string, double>> myList = Altern.ToList();

myList.Sort((firstPair, nextPair) =>
            {
               return firstPair.Value.CompareTo(nextPair.Value);
            });

foreach (KeyValuePair<string, double> pair in myList)
{
   write.WriteLine(pair.Key + ";" + pair.Value);
}
write.Close();
Console.WriteLine("TOPSIS ranking is written to TOPSIS_OUTPUT.csv");
```

Listing A-22. *C# cluster crossing finding algorithm for the given region*

```
Function GetClusterIntersections(ByVal Lat1 As Double, ByVal Lon1 As Double, ByVal Lat2 As Double,
ByVal Lon2 As Double, ptsCW() As Double) As Boolean
```

```
    ReDim ptsCW(1, 2, 2, 5) As Double
    Dim pts(5) As Double
    Dim f1 As Double
    Dim f2 As Double
    Dim l1 As Double
    Dim l2 As Double
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, 58.78, (Lon1 + Lon2) / 2 - 0.01, 58.78, (Lon1 + Lon2) / 2 + 0.01,
f1, l1, f2, l2)
    pts(3) = 0
    If Abs(f1 - 58.78) < Abs(f2 - 58.78) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If Lat1 < 58.78 And pts(1) < 5.035 Then
            pts(4) = 1
            pts(5) = 0
        ElseIf Lat1 >= 58.78 And pts(1) < 5.035 Then
            pts(4) = 0
            pts(5) = 1
        ElseIf Lat1 < 58.78 And pts(1) >= 5.035 Then
            pts(4) = 1
            pts(5) = 2
        ElseIf Lat1 >= 58.78 And pts(1) >= 5.035 Then
            pts(4) = 2
            pts(5) = 1
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, Lat1, 5.035, Lat2, 5.035, f1, l1, f2, l2)
    If Abs(f1 - 58.78) < Abs(f2 - 58.78) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    pts(3) = 0
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If pts(0) < 58.78 Then
            pts(4) = 1
            pts(5) = 1
        ElseIf pts(0) >= 58.78 And pts(0) < 59.04 Then
            If Lon1 < 5.035 Then
                pts(4) = 0
                pts(5) = 2
            Else
                pts(4) = 2
                pts(5) = 0
```

```
            End If
        ElseIf pts(0) >= 59.04 Then
            If Lon1 < 5.035 Then
                pts(4) = 0
                pts(5) = 1
            Else
                pts(4) = 1
                pts(5) = 0
            End If
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, 59.04, (Lon1 + Lon2) / 2 - 0.01, 59.04, (Lon1 + Lon2) / 2 + 0.01,
f1, l1, f2, l2)
    If Abs(f1 - 59.04) < Abs(f2 - 59.04) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    pts(3) = 0
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If pts(1) < 5.035 Then
            pts(4) = 0
            pts(5) = 0
        ElseIf Lat1 < 59.04 Then
            pts(4) = 2
            pts(5) = 1
        ElseIf Lat1 >= 59.04 Then
            pts(4) = 1
            pts(5) = 2
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, Lat1, 5.035, Lat2, 5.035, f1, l1, f2, l2)
    If Abs(f1 - 59.04) < Abs(f2 - 59.04) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    pts(3) = 1
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If Lon1 >= 5.035 Then
```

```
            pts(4) = 0
            pts(5) = 1
        ElseIf Lon1 < 5.035 Then
            pts(4) = 1
            pts(5) = 0
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, 58.28, (Lon1 + Lon2) / 2 - 0.01, 58.28, (Lon1 + Lon2) / 2 + 0.01, f1, l1, f2, l2)
    If Abs(f1 - 58.28) < Abs(f2 - 58.28) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    pts(3) = 1
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If Lat1 >= 58.28 And Lat1 < 58.44 And pts(1) < 2.105 Then
            pts(4) = 0
            pts(5) = 1
        ElseIf pts(1) < 2.105 Then
            pts(4) = 1
            pts(5) = 0
        ElseIf pts(1) >= 2.105 And pts(1) < 5.035 Then
            pts(4) = 1
            pts(5) = 1
        ElseIf pts(1) >= 5.035 Then
            pts(4) = 0
            pts(5) = 0
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, 58.44, (Lon1 + Lon2) / 2 - 0.01, 58.44, (Lon1 + Lon2) / 2 + 0.01, f1, l1, f2, l2)
    If Abs(f1 - 58.44) < Abs(f2 - 58.44) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    pts(3) = 1
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If Lat1 >= 58.28 And Lat1 < 58.44 And pts(1) < 2.105 Then
```

```
            pts(4) = 0
            pts(5) = 1
        ElseIf pts(1) < 2.105 Then
            pts(4) = 1
            pts(5) = 0
        ElseIf pts(1) >= 2.105 And pts(1) < 5.035 Then
            pts(4) = 1
            pts(5) = 1
        ElseIf pts(1) >= 5.035 Then
            pts(4) = 0
            pts(5) = 0
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    a = GetIntersection(Lat1, Lon1, Lat2, Lon2, Lat1, 2.105, Lat2, 2.105, f1, l1, f2, l2)
    If Abs(f1 - 58.44) < Abs(f2 - 58.44) Then
        pts(0) = f1
        pts(1) = l1
    Else
        pts(0) = f2
        pts(1) = l2
    End If
    pts(3) = 1
    If LiesBetween(Lat1, Lon1, pts(0), pts(1), Lat2, Lon2) Then
        pts(2) = GetDistance(Lat1, Lon1, pts(0), pts(1))
        If Lat1 >= 58.28 And Lat1 < 58.44 And pts(0) < 58.44 And pts(0) >= 58.28 Then
            pts(4) = 0
            pts(5) = 1
        ElseIf pts(0) < 58.44 And pts(0) >= 58.28 Then
            pts(4) = 1
            pts(5) = 0
        Else
            pts(4) = 1
            pts(5) = 1
        End If
        sshh = 0
        If ptsCW(pts(3), pts(4), pts(5), 2) <> 0 Then
            sshh = 3
        End If
        For i = 0 To 2
            ptsCW(pts(3), pts(4), pts(5), i + sshh) = pts(i)
        Next i
    End If
    GetClusterIntersections = True
End Function
```

Appendix B

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	1.666667	1.666667	1.666667	TBN3	0
OFP	1.666667	1.666667	1.666667	TBN3	0
WEP	2.10108	2.10107	2.23858	TBN3	0
SLE	2.23916	2.29167	2.49583	TBN3	0
DRA	2.56755	2.56755	2.6613	TBN3	0
OFP	3.05781	3.33333	3.66667	TBN3	0
FBS	3.05781	3.33333	3.66667	TBN3	0
OFP	3.05781	3.33333	3.66667	TBN3	0
WEP	4.10108	4.10107	4.23858	TBN3	0
SLE	4.23916	4.29167	4.49583	TBN3	0
VOL	4.51325	4.51325	4.65909	TBN3	0
OFP	5.08841	5.33333	6.66667	TBN3	0
FBS	5.08841	5.33333	6.66667	TBN3	0
OFP	5.08841	5.33333	6.66667	TBN3	0
WEP	7.10108	7.10108	7.23858	TBN3	0
SLE	7.23916	7.29167	7.49583	TBN3	0
GLI	7.57026	7.57026	7.73693	TBN3	0
OFP	8.17588	8.33333	8.66667	TBN3	0
FBS	8.17588	8.33333	8.66667	TBN3	0

Table B-1. *Schedule 1*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.666667	0.666667	0.666667	TBN1	0
OFP	0.666667	0.666667	0.666667	TBN1	0
WEP	1.18796	1.18796	1.32546	TBN1	0
SLE	1.32616	1.32616	1.53033	TBN1	0
DRA	1.61639	1.61639	1.71014	TBN1	0
OFP	2.18595	2.33333	3.66667	TBN1	0
FBS	2.18595	2.33333	3.66667	TBN1	0
OFP	2.18595	2.33333	3.66667	TBN1	0
WEP	4.18796	4.18796	4.32546	TBN1	0
SLE	4.32616	4.32616	4.53033	TBN1	0
GLI	4.61964	4.61964	4.78631	TBN1	0
OFP	5.31305	5.33333	5.66667	TBN1	0
FBS	5.31305	5.33333	5.66667	TBN1	0
OFP	5.31305	5.33333	5.66667	TBN1	0
WEP	6.18796	6.18796	6.32546	TBN1	0
SLE	6.32616	6.32616	6.53033	TBN1	0
VOL	6.55122	6.55122	6.69706	TBN1	0
OFP	7.21224	7.33333	7.66667	TBN1	0
FBS	7.21224	7.33333	7.66667	TBN1	0

Table B-2. *Schedule 2*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	1.666667	1.666667	1.666667	TBN1	0
OFP	1.666667	1.666667	1.666667	TBN1	0
WEP	2.10108	2.10107	2.23858	TBN1	0
SLE	2.23927	2.29167	2.49583	TBN1	0
DRA	2.56755	2.56755	2.6613	TBN1	0
OFP	3.13711	3.33333	3.66667	TBN1	0
FBS	3.13711	3.33333	3.66667	TBN1	0
OFP	3.13711	3.33333	3.66667	TBN1	0
WEP	4.10108	4.10107	4.23858	TBN1	0
SLE	4.23928	4.29167	4.49583	TBN1	0
VOL	4.51325	4.51325	4.65909	TBN1	0
OFP	5.17427	5.33333	5.66667	TBN1	0
FBS	5.17427	5.33333	5.66667	TBN1	0
OFP	5.17427	5.33333	5.66667	TBN1	0
WEP	6.10108	6.10108	6.23858	TBN1	0
SLE	6.23928	6.29167	6.49583	TBN1	0
GLI	6.57026	6.57026	6.73693	TBN1	0
OFP	7.26368	7.33333	8.66667	TBN1	0
FBS	7.26368	7.33333	8.66667	TBN1	0

Table B-3. *Schedule 3*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselId:
FBS	1.185947	1.333327	1.666667	TBN3	0
OFP	1.185947	1.333327	1.666667	TBN3	0
WEP	2.18796	2.18796	2.32546	TBN3	0
SLE	2.32616	2.32616	2.53032	TBN3	0
VOL	2.55123	2.55123	2.69706	TBN3	0
OFP	3.21224	3.33333	4.66667	TBN3	0
FBS	3.21224	3.33333	4.66667	TBN3	0
OFP	3.21224	3.33333	4.66667	TBN3	0
WEP	5.18796	5.18796	5.32546	TBN3	0
SLE	5.32616	5.32616	5.53033	TBN3	0
GLI	5.61964	5.61964	5.78631	TBN3	0
OFP	6.31305	6.33333	6.66667	TBN3	0
FBS	6.31305	6.33333	6.66667	TBN3	0
OFP	6.31305	6.33333	6.66667	TBN3	0
WEP	7.18796	7.18796	7.32546	TBN3	0
SLE	7.32616	7.32616	7.53033	TBN3	0
DRA	7.61639	7.61639	7.71014	TBN3	0
OFP	8.18595	8.33333	8.66667	TBN3	0
FBS	8.18595	8.33333	8.66667	TBN3	0

Table B-4. *Schedule 4*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.666667	0.666667	0.666667	TBN2	0
FBS	1.666667	1.666667	1.666667	TBN3	1
OFP	0.666667	0.666667	0.666667	TBN2	0
OFP	1.666667	1.666667	1.666667	TBN3	1
GRA	1.00879	1.0088	1.1338	TBN2	0
TRL	1.27121	1.27121	1.39204	TBN2	0
OVA	1.40533	1.40533	1.52617	TBN2	0
SLE	1.5741	1.5741	1.77827	TBN2	0
WEP	1.77885	1.77885	1.91635	TBN2	0
VOL	2.09528	2.09528	2.24111	TBN3	1
WEP	2.25795	2.25795	2.39545	TBN3	1
OFP	2.35005	3.33333	3.66667	TBN2	0
FBS	2.35005	3.33333	3.66667	TBN2	0
OFP	2.35005	3.33333	3.66667	TBN2	0
SLE	2.39602	2.39602	2.60019	TBN3	1
DRA	2.67227	2.67227	2.76602	TBN3	1
GDR	2.92301	2.92301	3.04385	TBN3	1
GRA	3.15098	3.15098	3.27598	TBN3	1
HDA	3.36551	3.36551	3.55301	TBN3	1
OFP	3.93771	4.33333	4.66667	TBN3	1
FBS	3.93771	4.33333	4.66667	TBN3	1
OFP	3.93771	4.33333	4.66667	TBN3	1
OVA	4.10783	4.10783	4.22866	TBN2	0
TRL	4.24196	4.24196	4.36279	TBN2	0
GLI	4.37926	4.37926	4.54593	TBN2	0
GDR	4.57405	4.57405	4.69488	TBN2	0
GRA	4.80202	4.80202	4.92702	TBN2	0
GRA	5.00879	5.0088	5.1338	TBN3	1
OFP	5.26915	5.33333	5.66667	TBN2	0
FBS	5.26915	5.33333	5.66667	TBN2	0
OFP	5.26915	5.33333	5.66667	TBN2	0
TRL	5.27121	5.27121	5.39204	TBN3	1
OVA	5.40533	5.40533	5.52617	TBN3	1
SLE	5.5741	5.5741	5.77827	TBN3	1
WEP	5.77885	5.77885	5.91635	TBN3	1
GRA	6.00879	6.0088	6.1338	TBN2	0
GDR	6.24093	6.24093	6.36177	TBN2	0
OFP	6.35005	7.33333	8.66667	TBN3	1
FBS	6.35005	7.33333	8.66667	TBN3	1
HDA	6.52549	6.52549	6.71299	TBN2	0
OFP	7.09769	7.33333	7.66667	TBN2	0
FBS	7.09769	7.33333	7.66667	TBN2	0

Table B-5. *Schedule 5*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.35	1.33333	1.666667	TBN2	1
FBS	1.35	2.33333	2.666667	TBN1	0
OFP	0.35	1.33333	1.666667	TBN2	1
OFP	1.35	2.33333	2.666667	TBN1	0
GRA	2.07722	2.07722	2.20222	TBN2	1
GDR	2.33078	2.33078	2.45162	TBN2	1
GLI	2.48537	2.48537	2.65203	TBN2	1
TRL	2.6718	2.6718	2.79263	TBN2	1
OVA	2.80858	2.80858	2.92942	TBN2	1
WEP	2.98629	2.98629	3.12379	TBN2	1
VOL	3.181	3.181	3.32683	TBN1	0
SLE	3.34773	3.34773	3.5519	TBN1	0
OVA	3.60942	3.60942	3.73025	TBN1	0
OFP	3.64423	4.33333	4.66667	TBN2	1
FBS	3.64423	4.33333	4.66667	TBN2	1
OFP	3.64423	4.33333	4.66667	TBN2	1
TRL	3.7462	3.7462	3.86704	TBN1	0
GDR	3.91743	3.91743	4.03826	TBN1	0
GRA	4.16683	4.16683	4.29183	TBN1	0
HDA	4.39925	4.39925	4.58675	TBN1	0
OFP	5.0484	5.33333	5.66667	TBN1	0
FBS	5.0484	5.33333	5.66667	TBN1	0
OFP	5.0484	5.33333	5.66667	TBN1	0
GRA	5.07722	5.07722	5.20222	TBN2	1
WEP	5.41456	5.41456	5.55206	TBN2	1
SLE	5.55276	5.55276	5.75692	TBN2	1
GRA	6.07722	6.07722	6.20222	TBN1	0
OFP	6.27756	6.33333	6.66667	TBN2	1
FBS	6.27756	6.33333	6.66667	TBN2	1
OFP	6.27756	6.33333	6.66667	TBN2	1
HDA	6.30965	6.30965	6.49715	TBN1	0
GDR	6.69362	6.69362	6.81445	TBN1	0
TRL	6.86485	6.86485	6.98568	TBN1	0
OVA	7.00163	7.00163	7.12246	TBN1	0
GRA	7.07722	7.07722	7.20222	TBN2	1
WEP	7.17934	7.17934	7.31684	TBN1	0
DRA	7.40375	7.40375	7.4975	TBN1	0
SLE	7.41519	7.41519	7.61935	TBN2	1
OFP	7.9729	8.33333	9.66667	TBN1	0
FBS	7.9729	8.33333	9.66667	TBN1	0
FBS	8.13999	8.33333	8.66667	TBN2	1
OFP	8.13999	8.33333	8.66667	TBN2	1

Table B-6. *Schedule 6*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.09769	0.33333	0.666667	TBN3	1
FBS	0.35	1.33333	1.666667	TBN1	0
OFP	0.09769	0.33333	0.666667	TBN3	1
OFP	0.35	1.33333	1.666667	TBN1	0
GRA	1.00879	1.0088	1.1338	TBN3	1
DRA	1.33727	1.33727	1.43102	TBN3	1
SLE	1.5031	1.5031	1.70726	TBN3	1
WEP	1.70785	1.70785	1.84535	TBN3	1
OVA	1.89274	1.89274	2.01357	TBN3	1
TRL	2.02687	2.02687	2.1477	TBN3	1
VOL	2.09528	2.09528	2.24111	TBN1	0
SLE	2.25853	2.29167	2.49583	TBN1	0
GLI	2.57026	2.57026	2.73693	TBN1	0
OFP	2.58184	3.33333	3.66667	TBN3	1
FBS	2.58184	3.33333	3.66667	TBN3	1
OFP	2.58184	3.33333	3.66667	TBN3	1
TRL	2.7534	2.7534	2.87424	TBN1	0
GDR	2.91623	2.91623	3.03706	TBN1	0
GRA	3.1442	3.1442	3.2692	TBN1	0
HDA	3.35872	3.35872	3.54622	TBN1	0
OFP	3.93093	4.33333	4.66667	TBN1	0
FBS	3.93093	4.33333	4.66667	TBN1	0
OFP	3.93093	4.33333	4.66667	TBN1	0
WEP	4.10036	4.10036	4.23786	TBN3	1
OVA	4.28526	4.28526	4.40609	TBN3	1
GDR	4.46086	4.46086	4.58169	TBN3	1
GRA	4.68883	4.68883	4.81383	TBN3	1
GRA	5.00879	5.0088	5.1338	TBN1	0
OFP	5.15596	5.33333	5.66667	TBN3	1
FBS	5.15596	5.33333	5.66667	TBN3	1
OFP	5.15596	5.33333	5.66667	TBN3	1
TRL	5.27121	5.27121	5.39204	TBN1	0
OVA	5.40533	5.40533	5.52617	TBN1	0
SLE	5.5741	5.5741	5.77827	TBN1	0
WEP	5.77885	5.77885	5.91635	TBN1	0
GRA	6.00879	6.0088	6.1338	TBN3	1
GDR	6.24093	6.24093	6.36177	TBN3	1
OFP	6.35005	7.33333	8.66667	TBN1	0
FBS	6.35005	7.33333	8.66667	TBN1	0
HDA	6.52549	6.52549	6.71299	TBN3	1
OFP	7.09769	7.33333	7.66667	TBN3	1
FBS	7.09769	7.33333	7.66667	TBN3	1

Table B-7. *Schedule 7*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.09769	0.33333	0.666667	TBN3	1
FBS	0.35	1.33333	1.666667	TBN2	0
OFP	0.09769	0.33333	0.666667	TBN2	0
OFP	0.35	1.33333	1.666667	TBN2	0
SLE	1.1873	1.29167	1.49583	TBN3	1
OVA	1.54377	1.54377	1.6646	TBN3	1
TRL	1.67789	1.67789	1.79872	TBN3	1
GDR	1.84072	1.84072	1.96155	TBN3	1
GRA	2.06869	2.06869	2.19369	TBN3	1
WEP	2.10036	2.10036	2.23786	TBN2	0
HDA	2.29167	2.29167	2.47917	TBN3	1
GLI	2.31173	2.31173	2.4784	TBN2	0
GDR	2.50652	2.50652	2.62735	TBN2	0
GRA	2.73449	2.73449	2.85949	TBN2	0
OFP	2.94081	3.33333	4.66667	TBN3	1
FBS	2.94081	3.33333	4.66667	TBN3	1
OFP	2.94081	3.33333	4.66667	TBN3	1
OFP	3.27004	3.33333	3.66667	TBN2	0
FBS	3.27004	3.33333	3.66667	TBN2	0
OFP	3.27004	3.33333	3.66667	TBN2	0
GRA	4.00879	4.0088	4.1338	TBN2	0
TRL	4.27121	4.27121	4.39204	TBN2	0
OVA	4.40533	4.40533	4.52617	TBN2	0
SLE	4.5741	4.5741	4.77827	TBN2	0
WEP	4.77885	4.77885	4.91635	TBN2	0
SLE	5.1873	5.29167	5.49583	TBN3	1
OFP	5.43678	6.33333	6.66667	TBN2	0
FBS	5.43678	6.33333	6.66667	TBN2	0
OFP	5.43678	6.33333	6.66667	TBN2	0
OVA	5.54377	5.54377	5.6646	TBN3	1
TRL	5.67789	5.67789	5.79873	TBN3	1
GDR	5.84072	5.84072	5.96155	TBN3	1
GRA	6.06869	6.06869	6.19369	TBN3	1
HDA	6.29167	6.29167	6.47917	TBN3	1
OFP	6.94081	7.33333	7.66667	TBN3	1
FBS	6.94081	7.33333	7.66667	TBN3	1
GRA	7.00879	7.0088	7.1338	TBN2	0
VOL	7.29556	7.29556	7.4414	TBN2	0
WEP	7.45823	7.45823	7.59573	TBN2	0
DRA	7.66816	7.66816	7.76191	TBN2	0
OFP	8.23731	8.33333	8.66667	TBN2	0
FBS	8.23731	8.33333	8.66667	TBN2	0

Table B-8. *Schedule 8*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.35	1.33333	1.666667	TBN2	0
FBS	1.35	2.33333	2.666667	TBN3	1
OFP	0.35	1.33333	1.666667	TBN2	0
OFP	1.35	2.33333	2.666667	TBN3	1
GRA	2.00879	2.0088	2.1338	TBN2	0
WEP	2.31075	2.31075	2.44825	TBN2	0
SLE	2.44882	2.44883	2.65299	TBN2	0
GRA	3.00879	3.0088	3.1338	TBN3	1
OFP	3.16667	3.33333	3.66667	TBN2	0
FBS	3.16667	3.33333	3.66667	TBN2	0
OFP	3.16667	3.33333	3.66667	TBN2	0
HDA	3.24122	3.29167	3.47917	TBN3	1
GDR	3.64289	3.64289	3.76372	TBN3	1
TRL	3.80572	3.80572	3.92655	TBN3	1
OVA	3.93985	3.93985	4.06068	TBN3	1
GRA	4.00879	4.0088	4.1338	TBN2	0
WEP	4.31075	4.31075	4.44825	TBN2	0
SLE	4.44883	4.44883	4.65299	TBN2	0
OFP	4.59007	5.33333	6.66667	TBN3	1
FBS	4.59007	5.33333	6.66667	TBN3	1
OFP	4.59007	5.33333	6.66667	TBN3	1
OFP	5.16667	5.33333	5.66667	TBN2	0
FBS	5.16667	5.33333	5.66667	TBN2	0
OFP	5.16667	5.33333	5.66667	TBN2	0
GRA	6.00879	6.0088	6.1338	TBN2	0
GDR	6.24093	6.24093	6.36177	TBN2	0
GLI	6.38989	6.38989	6.55655	TBN2	0
TRL	6.57303	6.57303	6.69386	TBN2	0
OVA	6.70715	6.70715	6.82799	TBN2	0
VOL	6.8608	6.8608	7.00663	TBN2	0
WEP	7.02347	7.02347	7.16097	TBN2	0
SLE	7.1873	7.29167	7.49583	TBN3	1
DRA	7.24788	7.29167	7.38542	TBN2	0
OVA	7.54377	7.54377	7.6646	TBN3	1
TRL	7.67789	7.67789	7.79873	TBN3	1
GDR	7.84072	7.84072	7.96155	TBN3	1
OFP	7.86081	8.33333	8.66667	TBN2	0
FBS	7.86081	8.33333	8.66667	TBN2	0
GRA	8.06869	8.06869	8.19369	TBN3	1
HDA	8.29167	8.29167	8.47917	TBN3	1
OFP	8.94081	9.33333	9.66667	TBN3	1
FBS	8.94081	9.33333	9.66667	TBN3	1

Table B-9. *Schedule 9*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.09769	0.33333	0.666667	TBN2	0
FBS	1.35	2.33333	2.666667	TBN3	1
OFP	0.09769	0.33333	0.666667	TBN2	0
OFP	1.35	2.33333	2.666667	TBN3	1
VOL	1.181	1.181	1.32683	TBN2	0
SLE	1.34773	1.34773	1.5519	TBN2	0
OVA	1.60942	1.60942	1.73025	TBN2	0
TRL	1.7462	1.7462	1.86704	TBN2	0
GDR	1.91743	1.91743	2.03826	TBN2	0
GRA	2.16683	2.16683	2.29183	TBN2	0
HDA	2.39925	2.39925	2.58675	TBN2	0
GRA	3.03743	3.03743	3.16243	TBN3	1
OFP	3.0484	3.33333	3.66667	TBN2	0
FBS	3.0484	3.33333	3.66667	TBN2	0
OFP	3.0484	3.33333	3.66667	TBN2	0
WEP	3.35419	3.35419	3.49169	TBN3	1
SLE	3.49232	3.49232	3.69649	TBN3	1
GRA	4.07722	4.07722	4.20222	TBN2	0
OFP	4.16667	4.33333	4.66667	TBN3	1
FBS	4.16667	4.33333	4.66667	TBN3	1
OFP	4.16667	4.33333	4.66667	TBN3	1
HDA	4.30965	4.30965	4.49715	TBN2	0
GDR	4.69362	4.69362	4.81445	TBN2	0
TRL	4.86485	4.86485	4.98568	TBN2	0
OVA	5.00163	5.00163	5.12246	TBN2	0
GRA	5.07722	5.07722	5.20222	TBN3	1
WEP	5.17934	5.17934	5.31684	TBN2	0
DRA	5.40375	5.40375	5.4975	TBN2	0
SLE	5.41519	5.41519	5.61935	TBN3	1
OFP	5.9729	6.33333	7.66667	TBN2	0
FBS	5.9729	6.33333	7.66667	TBN2	0
OFP	6.13999	6.33333	6.66667	TBN3	1
FBS	6.13999	6.33333	6.66667	TBN3	1
OFP	6.13999	6.33333	6.66667	TBN3	1
GRA	7.07722	7.07722	7.20222	TBN3	1
GDR	7.33078	7.33078	7.45162	TBN3	1
GLI	7.48537	7.48537	7.65203	TBN3	1
TRL	7.6718	7.6718	7.79263	TBN3	1
OVA	7.80858	7.80858	7.92942	TBN3	1
WEP	7.98629	7.98629	8.12379	TBN3	1
OFP	8.64423	9.33333	9.66667	TBN3	1
FBS	8.64423	9.33333	9.66667	TBN3	1

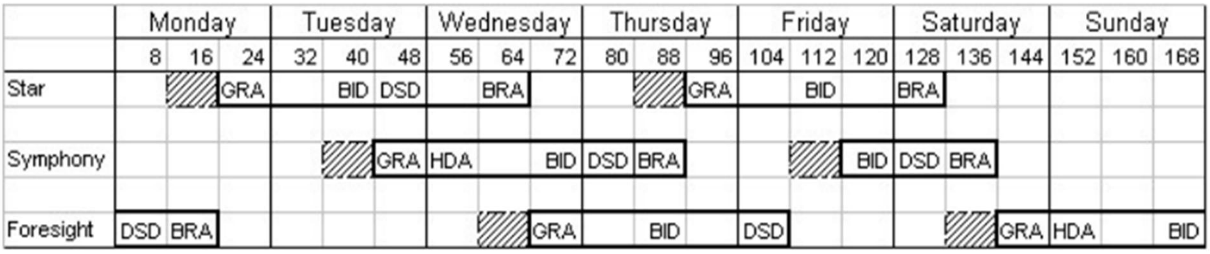
Table B-10. *Schedule 10*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	0.09769	0.33333	0.666667	TBN2	1
FBS	0.35	1.33333	1.666667	TBN1	0
OFP	0.09769	0.33333	0.666667	TBN2	1
OFP	0.35	1.33333	1.666667	TBN1	0
GRA	1.07722	1.07722	1.20222	TBN2	1
HDA	1.30965	1.30965	1.49715	TBN2	1
GDR	1.69362	1.69362	1.81445	TBN2	1
TRL	1.86485	1.86485	1.98568	TBN2	1
OVA	2.00163	2.00163	2.12246	TBN2	1
GRA	2.07722	2.07722	2.20222	TBN1	0
WEP	2.17934	2.17934	2.31684	TBN2	1
DRA	2.40375	2.40375	2.4975	TBN2	1
SLE	2.41519	2.41519	2.61935	TBN1	0
OFP	2.9729	3.33333	4.66667	TBN2	1
FBS	2.9729	3.33333	4.66667	TBN2	1
OFP	2.9729	3.33333	4.66667	TBN2	1
OFP	3.13999	3.33333	3.66667	TBN1	0
FBS	3.13999	3.33333	3.66667	TBN1	0
OFP	3.13999	3.33333	3.66667	TBN1	0
GRA	4.07722	4.07722	4.20222	TBN1	0
GDR	4.33078	4.33078	4.45162	TBN1	0
GLI	4.48537	4.48537	4.65203	TBN1	0
TRL	4.6718	4.6718	4.79263	TBN1	0
OVA	4.80858	4.80858	4.92942	TBN1	0
WEP	4.98629	4.98629	5.12379	TBN1	0
VOL	5.181	5.181	5.32683	TBN2	1
SLE	5.34773	5.34773	5.5519	TBN2	1
OVA	5.60942	5.60942	5.73025	TBN2	1
OFP	5.64422	6.33333	6.66667	TBN1	0
FBS	5.64422	6.33333	6.66667	TBN1	0
OFP	5.64422	6.33333	6.66667	TBN1	0
TRL	5.7462	5.7462	5.86704	TBN2	1
GDR	5.91743	5.91743	6.03826	TBN2	1
GRA	6.16683	6.16683	6.29183	TBN2	1
HDA	6.39925	6.39925	6.58675	TBN2	1
GRA	7.00879	7.0088	7.1338	TBN1	0
OFP	7.0484	7.33333	7.66667	TBN2	1
FBS	7.0484	7.33333	7.66667	TBN2	1
WEP	7.31075	7.31075	7.44825	TBN1	0
SLE	7.44882	7.44883	7.65299	TBN1	0
OFP	8.08686	8.33333	8.66667	TBN1	0
FBS	8.08686	8.33333	8.66667	TBN1	0

Table B-11. *Schedule 11*

Inst:	Arr:	Disch:	Depart:	Vessel:	VesselID:
FBS	1.666667	1.666667	1.666667	TBN3	1
FBS	2.66667	2.66667	2.66667	TBN1	0
OFP	1.666667	1.666667	1.666667	TBN3	1
OFP	2.66667	2.66667	2.66667	TBN1	0
GRA	2.07722	2.07722	2.20222	TBN3	1
GDR	2.33078	2.33078	2.45162	TBN3	1
GLI	2.48537	2.48537	2.65203	TBN3	1
TRL	2.6718	2.6718	2.79263	TBN3	1
OVA	2.80858	2.80858	2.92942	TBN3	1
WEP	2.98629	2.98629	3.12379	TBN3	1
VOL	3.181	3.181	3.32683	TBN1	0
SLE	3.34773	3.34773	3.5519	TBN1	0
OVA	3.60942	3.60942	3.73025	TBN1	0
OFP	3.64423	4.33333	4.66667	TBN3	1
FBS	3.64423	4.33333	4.66667	TBN3	1
OFP	3.64423	4.33333	4.66667	TBN3	1
TRL	3.7462	3.7462	3.86704	TBN1	0
GDR	3.91743	3.91743	4.03826	TBN1	0
GRA	4.16683	4.16683	4.29183	TBN1	0
HDA	4.39925	4.39925	4.58675	TBN1	0
OFP	5.0484	5.33333	5.66667	TBN1	0
FBS	5.0484	5.33333	5.66667	TBN1	0
OFP	5.0484	5.33333	5.66667	TBN1	0
GRA	5.07722	5.07722	5.20222	TBN3	1
WEP	5.41456	5.41456	5.55206	TBN3	1
SLE	5.55276	5.55276	5.75692	TBN3	1
GRA	6.07722	6.07722	6.20222	TBN1	0
OFP	6.27756	6.33333	6.66667	TBN3	1
FBS	6.27756	6.33333	6.66667	TBN3	1
OFP	6.27756	6.33333	6.66667	TBN3	1
HDA	6.30965	6.30965	6.49715	TBN1	0
GDR	6.69362	6.69362	6.81445	TBN1	0
TRL	6.86485	6.86485	6.98568	TBN1	0
OVA	7.00163	7.00163	7.12246	TBN1	0
GRA	7.07722	7.07722	7.20222	TBN3	1
WEP	7.17934	7.17934	7.31684	TBN1	0
DRA	7.40375	7.40375	7.4975	TBN1	0
SLE	7.41519	7.41519	7.61935	TBN3	1
OFP	7.9729	8.33333	9.66667	TBN1	0
FBS	7.9729	8.33333	9.66667	TBN1	0
OFP	8.13999	8.33333	8.66667	TBN3	1
FBS	8.13999	8.33333	8.66667	TBN3	1

Table B-12. *Schedule 12*



	Monday			Tuesday			Wednesday			Thursday			Friday			Saturday			Sunday		
	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128	136	144	152	160	168
Star		▨	GRA		BID	DSD		BRA			▨	GRA		BID		BRA					
Symphony					▨	GRA	HDA		BID	DSD	BRA			▨	BID	DSD	BRA				
Foresight	DSD	BRA						▨	GRA		BID		DSD				▨	GRA	HDA		BID

Figure B-1. *Example of a schedule in the form of Gant chart* (adopted from Shyshou et al. (2012))