NATIONAL TECHNICAL UNIVERSITY OF ATHENS
School of Naval Architecture and Marine Engineering
Department of Ship Design and Maritime Transport

Diploma Thesis:

On the Estimation of the Propulsion Power of a VLCC Tanker Based on Operational Data

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Abstract

The purpose of this thesis is to develop a real-time vessel performance analysis system to evaluate the condition of ships with respect to their clean hull and clean propeller condition. During operation, the vessel will experience an increase of resistance due to several factors, linked to the sailing conditions. Added wave resistance, wind resistance, shallow water effect and trim are examples of parameters, which affect the power (energy) needed to propel the vessel. Any increase in resistance will result to the increase of fuel consumption and thus the increase of harmful emissions to the environment. A robust monitoring and analysis system can be used as a supporting tool to decisions related to actions aiming to improve performance. The performance evaluation is based on a vessel-specific model which takes into account operational and weather condition, trying to assess and estimate power needed to overcome all resistance components, while assuming a clean hull and propeller.

The current thesis is based on the analysis of data, logged through the automated data transmission system of sensors' onboard a 319,000 tdw VLCC managed by Maran Tankers Management Inc. Through mapping of these parameters to the output target (the shaft power measured by a torque meter) the model is generated.

The goal of the developed system is to investigate the potential use of Artificial Neural Networks (ANNs) in estimating the power needed to propel the vessel in any given operational, environmental and loading condition, assuming a clean hull and clean propeller condition. Multi-layer perceptron (MLP) networks, were selected to model the vessel's behaviour.

The increasing amount of data transmitted to shore is creating the opportunity to develop systems based on information that until recently was not available. ANNs and in particular, MLPs, are an effective way to process this information. The results indicate that such an approach could be successfully applied, giving the potential to approximate complex non-linear regression problems, based on a reliable set of measured data.

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I. Motivation & Introduction

A. Introduction

The international shipping industry is responsible for the carriage of about 80-90% of world trade by volume and more than 70% by value, making seaborne trade a vital mode of transport supporting global economy and growth (ICS, 2015). Shipping is an international industry subject to a global regulatory framework aiming to ensure safety and environmental protection.

In the recent years a lot of shipping companies as well as charterers, involved in long time chartering gain interest in monitoring the performance of their vessels, in order to reduce their maintenance and operational costs. The past years, the high fuel oil price and the potential savings of a good management of the vessel was the key to a successful operation. In our days, with the low freights, a good performing vessel could make the difference to a beneficial deal for all parties.

The competitive environment, the overcapacity of the industry, as well as the rocketing of oil price in the period 2004-2014, as demonstrated at the graph below, made stakeholders agree that the monitoring, evaluation and optimization of ship performance play a vital role in the profitability of the business.

Figure I-1 West Texas Intermediate(WTI or NYMEX) crude oil prices per barrel. (Macrotrends, n.d.)

Energy efficiency is achieved primarily through well-planned and properly managed ship operations with the continuous commitment of the onshore as well as the onboard personnel. To make it successful, the energy management and the performance monitoring and evaluation should exceed the mere implementation of the rules and regulation and aim for the minimization of energy consumption, with sophisticated systems based on business, as well as physical models.

Efforts from international organizations (European Environment Agency, International Maritime Organization, etc.) to increase environmental awareness and reduce emissions and energy consumption had a vast impact in the improvement of the regulatory background of shipping industry. Shipping offers a substantially lower carbon intensity than the other freight modes, in terms of emissions and fuel consumption. Results derived in the framework of the third IMO GHG study are presented in the following table, where CO_2e describes the combination of CO_2, CH_4 and N_2O gases emitted.

Third IMO GHG Study 2014 CO_2					
Year	**Global CO_2**	**Total shipping**	**% of global**	**International shipping**	**% of global**
2007	31,409	1,100	3.50%	885	2.80%
2008	32,204	1,135	3.50%	921	2.90%
2009	32,047	978	3.10%	855	2.70%
2010	33,612	915	2.70%	771	2.30%
2011	34,723	1,022	2.90%	850	2.40%
2012	35,640	938	2.60%	796	2.20%
Average	**33,273**	**1,015**	**3.10%**	**846**	**2.60%**
Third IMO GHG Study 2014 CO_2e					
Year	**GlobalCO_2e**	**Total shipping**	**%of global**	**International shipping**	**%of global**
2007	34,881	1,121	3.20%	903	2.60%
2008	35,677	1,157	3.20%	940	2.60%
2009	35,519	998	2.80%	873	2.50%
2010	37,085	935	2.50%	790	2.10%
2011	38,196	1,045	2.70%	871	2.30%
2012	39,113	961	2.50%	816	2.10%
Average	**36,745**	**1,036**	**2.80%**	**866**	**2.40%**

Table I-1 a) Shipping CO_2 emissions compared with global CO_2 emissions(values in million tons) and b) Shipping GHGs (in CO_2e) compared with global GHGs (values in million tons) (IMO, Reduction of GHG Emissions from Ships, 2014)

However, additional measures have been taken for the further improvement of the energy efficiency of ship related operations, to achieve a level of efficiency near the current industry leaders within each ship type and trade. This topic, has been discussed in detail in a number of IMO working groups as well as Marine Environmental Protection Committees (MEPC). Shipping industry has improved in terms of emissions intensity, however the increasing demand of global trade and volume of transferred goods, drove to an increase in absolute terms of greenhouse gases emitted, as demonstrated at the graph below.

Figure I-2 : Change in CO_2 emissions and CO_2 intensity per type of vessel between 2013 to 2015 (Naya Olmer, 2017)

A lot of initiatives have been taken to push shipping towards a more efficient and environment friendly industry. This policy resulted in major changes in the design process and in the operation of vessels, with a great impact at the emissions density. However, the increasing number of vessels and the increase in their size in order to cover the rising demand of seaborne trade and transportation, resulted in an increase of the total mass of emissions (Naya Olmer, 2017).

Due to the large number of different parties involved, a complex and competing regulatory background has been established, which could be separated to international rules (IMO), international but region specific (European Union, European Environment Agency), national (flag state, flag administrations, United States Environment Protection Agency, United States Coast Guard), state (California's Air Resources Board), subnational-regional (San Pedro Bay country) as well as local (Port-Port State) legislation.

In this chapter, we will focus on Chapter 4 of MARPOL Annex VI, part of IMO regulations, the international convention for prevention of pollution from ships, and then specifically explain the Energy Efficiency Design Index (EEDI), Ship Energy Efficiency Management Plan (SEEMP) and Energy Efficiency Operational Indicator (EEOI) using the relevant IMO guidelines.

The referred Annex is dealing with air pollution from ships and the aim of its revision, is to progressively reduce globally the emission of pollutant gases, such as Sulphur oxides (SO_x), Nitric oxides (NO_x), particulate matters and carbon dioxide (CO_2). A schematic representation of the major events taken place the last twenty years, in order to drive shipping into a more environmental friendly and energy efficient regulatory framework, is presented.

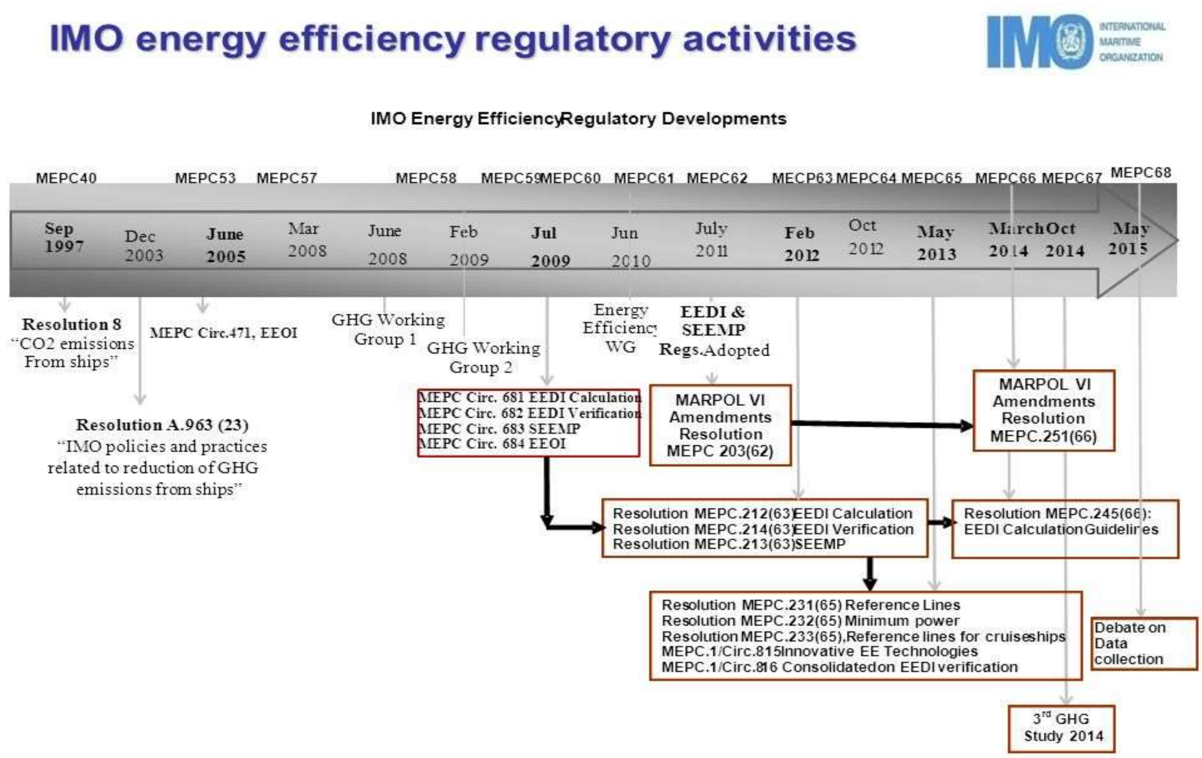


Figure I-3 : IMO energy efficiency regulatory activities (IMO, Ship Energy Efficiency Regulations and Related Guidelines, 2016)

The revised edition of MARPOL Annex VI, which will be in effect from 1st of January 2020, will reduce the global Sulphur cap from the current 3.50% m/m (mass/mass) to 0.50% m/m in areas other than ECAs. This will affect directly shipping and oil market, as fuel of "better" quality and more expensive distill products will be required from the refineries. Big investments will be made, either by the refineries, which will alter their production and supply chain, in order to comply with the market demand, as shipping is the main consumer of heavy fuel oil, a byproduct of refineries production chain, or by ship owners in order to acquire technologies that could result in emissions equivalent to a low Sulphur content fuel by burning heavy oil distills.

Also, in the framework of the progressive reduction in NO_x emissions of marine engines, vessels constructed on or after 1st of January 2016 have to comply with the stringent "Tier III" emission limits compared to the "Tier II" limits for vessels constructed on or after 1st of January 2011.

As for the greenhouse gases (GHG), CO_2, regulatory background is more complex. MARPOL Annex VI introduced two mandatory mechanisms as energy efficiency standards for ships, which aim to improve ship design and operation in terms of emissions related to global warming. These regulatory mechanisms are:

- Energy Efficiency Design Index (EEDI), for new ships;
- Ship Energy Efficiency Management Plan (SEEMP), for all ships.

Additionally, one non-mandatory, element has been introduced by IMO, which is intended to act as an indicator of the overall operational energy efficiency.

- Energy Efficiency Operational Indicator (EEOI).

1. Energy Efficiency Design Index (EEDI)

EEDI is an index related to the mass of CO_2 generated by the vessel in order to fulfill its transport work (tons-mile), calculated for a specific operational condition. IMO regulated limits to this index based on vessel type and size, intending to drive ship technologies to more energy efficient solutions over time. According to Chapter 4 of MARPOL Annex VI, this index is applied to all ships of 400 gross tonnage or greater, of the following types:

- Bulk carrier
- Gas carrier (none LNG carriers)
- Tanker
- Container ship
- General cargo ship
- Refrigerated cargo ship
- Combination carrier
- Ro-Ro cargo ships (vehicle carrier)
- Ro-Ro cargo ships
- Ro-Ro Passenger ship
- LNG carrier
- Cruise passenger ships (having non-conventional propulsion)

As IMO is an international organization, all vessels engaged in international routes should comply to its standards. Regulation 21 specifies the methodology for calculation of the required EEDI and all relevant details. The regulatory limit of the Index, is calculated by the use of the reference lines and the use of the corresponding reduction factor linked to the implementation phase of the regulation, applied to the corresponding reference line per ship type.

The reference line is calculated by the following equation,

$$ReferenceEEDI = a \cdot b^{-c}$$

where,

b: ship capacity

a & c: parameters for determination of EEDI reference value for each ship type, included in the Regulation 21[Resolution MEPC. 203(62) and MEPC.251(66)]

ReferenceEEDI: Reference value of EEDI

Reduction factors, or CO_2 reduction levels are established in order to gradually reduce the intensity of CO_2 emissions in four stages, following and supporting technological and operational innovation. Owners, ship designers and yards are free to choose the technologies to satisfy the EEDI requirement in the designed operational condition. The concept of EEDI is the progressive reduction of the corresponding Index limit through the years, after assessing technologies available at the market, which for the time being has 4 phases.

Phase 0, 0% reduction factor, data collection 2013-2015;
Phase 1, 10% reduction factor: 2015-2020;
Phase 2, 15% or 20% reduction factor depending vessel type and size: 2020-2025;
Phase 3, 30% reduction factor: 2025
Reduction factor is applied on the corresponding EEDI reference line of the vessel type and deadweight (DWT) as following:

$$RequiredEEDI = (1 - \frac{X}{100}) \cdot ReferenceEEDI$$

Where,

X: is the reduction factor of the implementation phase.

RequiredEEDI: The regulatory limit of the ship's EEDI, which the attained EEDI must not exceed.

A graphical representation of the different stages is demonstrated below.

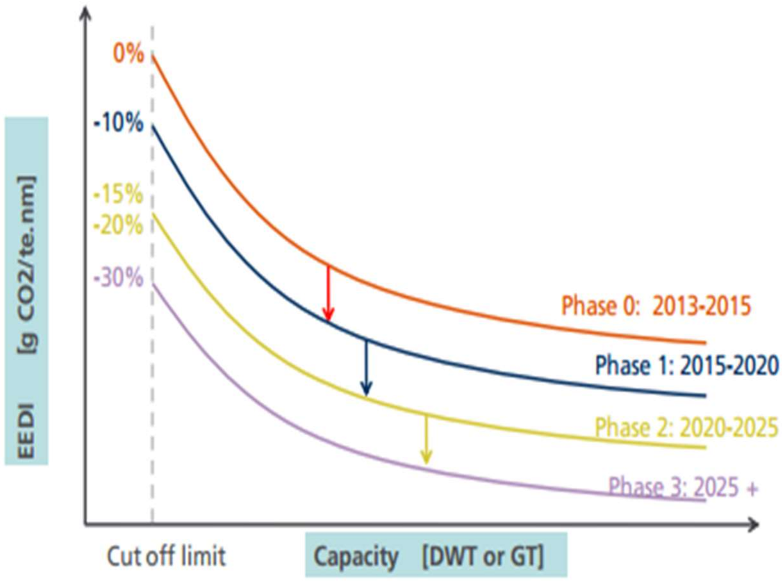


Figure I-4 : Reduction factors (IMO, Ship Energy Efficiency and Related Guidelines, 2016)

The attained EEDI is a vessel specific Index, provided by the yard, as part of the official documents of the ship, which demonstrates the equivalent CO_2 emissions on the designed operational condition.

$$AttainedEEDI = \frac{equivalent\ CO_2\ emissions\ for\ propulsion\ and\ auxiliaries}{transport\ work}$$

The equivalent CO_2 emissions are calculated for the estimated power at the design condition and the corresponding Specific Fuel Consumption (SFC) of every engine at that specific load and the conversion to gCO_2 emission is achieved by factors linked to fuel type. The effect of shaft motors or any innovative technologies used for power generation or technologies assisting propulsion or increasing propulsion efficiency are taken into account at the calculation of EEDI. Transport work is estimated by the capacity of the vessel at the design condition multiplied by the design speed of the vessel. Vessel type specific factors as well as, factors for vessels engaged at special trade routes (e.g. ice class vessels) and weather correction factors are inserted at the calculation stage. The detailed formula for EEDI and the definition of all factors included is demonstrated at (IMO, Resolution MEPC.245(66), 2014) . To fulfill EEDI requirement, the final attained EEDI must be equal or less than the required.

2. Ship Energy Efficiency Management Plan (SEEMP)

SEEMP, on the other hand, is a management tool as per MARPOL Annex VI Regulation 22, which establishes a mechanism for ship operators, ship-owners and crew to improve the energy efficiency of their vessels during their operational lifecycle. As a mechanism, is not as strict as EEDI and covers a wide range of different operational conditions including geographical parameters and commercial profile.

In most companies, it forms part of the ship's Safety Management System (SMS) and the Environmental Management System (EnMS), which is defined by the International Safety Management Code (ISM Code).

SEEMP's implementation is recommended to be developed in a manner of limited on-board administrative burden, as much as possible, and be managed by the onshore personnel and the systems of the company. The purpose of its implementation is not to establish limits or baselines, but to develop procedures and drive the company's policy to manage the on-going and long run environmental performance of vessels. It is a dynamic document, based on continuous updating and improvement of the performance system and feedback for every particular vessel. Evaluation and future energy improvement measures are produced by comparing the company's baseline-goals with its actual performance. Additional measures, in order to fulfill company's goals and improve the effectiveness of the already implemented measures are identified by this process. Continuous monitoring of the progress in the optimizing process creates an energy efficiency awareness policy among all parties (IMO, Ship Energy Efficiency and Related Guidelines, 2016).

3. Energy Efficiency Operational Indicator (EEOI)

As mentioned earlier, EEOI is a voluntary measure by the current regulations. However, it is recommended as an "energy efficiency performance indicator" during the operational phase of the ship and can be used to monitor the overall ship energy performance. The main goal of this indicator is to enable monitoring and evaluate efficiency and effects of any changes made to the vessels' operation in order to assist stakeholders in collecting information on the outcome of such variation and experience in a wider range of ship's operational profile.

EEOI, similarly defined as EEDI, represents the mass of emissions of carbon dioxides per unit of cargo-mile transport service and is advocated to be used as an indicator of a monitoring tool, included in the SEEMP, covering the wide range of energy efficiency and emission control through the real life cycle and operation of any vessel (IMO, MEPC.1/Circ.684, 2009).

The basic expression for EEOI for any voyage is defined as:

$$EEOI = \frac{\sum_j (FC_j \cdot C_{Fj})}{m_{Cargo} \cdot D}$$

Where,
j is the fuel type;
FC_j is the mass of the consumed fuel of j type at the particular voyage;
C_{Fj} is the fuel mass to CO_2 mass conversion factor for the j type fuel;
m_{cargo} is the cargo carried (tons) or work done (number of TEU or passengers), or gross tons for passenger ships;
D is the distance in nautical miles corresponding to the cargo carried or work done.
Similarly defined, the average of the indicator for a period or for a number of voyages can be obtained. This average is expressing the operational efficiency of the subject vessel for the specific time period EEOI is calculated.

The concept and main goal of this indicator, is that a ship could reduce its consumption using a system that could evaluate parameters, which affect its efficiency, and quantify the impact of each, to the overall result.

EEOI, is based on an easy to implement, easy to use methodology on an overall efficiency basis.

Recently, a discussion has been raised (Bertram, 2017) that a new indicator is necessary to trace the effect of the roughness of the hull and propeller surface, along with other parameters, on the consumption, taking into account the loading and operational condition.

The approach of a new indicator, focusing at the vessel's technical particulars, is to keep track of the energy efficiency of the ship and identify the operational parameters that cause any apparent deviation (Gregory Grigoropoulos, 2012).

B. International Standards

In addition to complying with the regulatory framework, market leading companies in order to be more competitive and attractive to charterers apply measures to harmonize their management with International Standards as ISO 14001 or/and ISO 50001. Environmental Management System or Energy Management System in case of ISO 50001 contain ship-specific procedures and measures similar to what is requested for SEEMP. Their goal is to monitor and control vessel performance based on feedback features, identify improvement and assist decision making when necessary, on a stricter manner. As a result, monitoring of operational-environmental efficiency is treated as an integral element of vessel management.

1. ISO 14001-Environmental Management

The latest revision of ISO 14001:2015 specifies the requirements for an environmental management system that an organization can use to enhance its environmental performance. It is intended for use by an organization seeking to manage its environmental responsibilities in a systematic manner that contributes to the environmental pillar of sustainability.

ISO 14001:2015 helps companies achieve the intended outcomes of its environmental management system, which provide value for the environment, the organization itself and interested parties. Consistent with the organization's environmental policy, the intended outcomes of an environmental management system include:

- enhancement of environmental performance;
- fulfilment of compliance obligations;
- achievement of environmental objectives.

ISO 14001:2015 is applicable to any organization, regardless of size, type and nature, and applies to the environmental aspects of its activities, products and services that the organization can either control or influence considering a life cycle perspective. ISO 14001:2015 does not state specific environmental performance criteria, but acts as a supporting tool to improve performance of the company and fulfill its commitment to systematically improve environmental management. Claims of conformity to ISO 14001:2015, are not acceptable unless all its requirements are incorporated into an organization's environmental management system and fulfilled without exclusion (ISO, Environmental Management, 2015).

2. ISO 50001-Energy Management

Enhancing energy efficiently helps organizations save money and contributes to conserve resources and tackle climate change. ISO 50001 supports organizations to use energy more efficiently, through the development of an energy management system (EnMS). Application of such standards contributes to more efficient use of energy, to enhance competitiveness and to reduce greenhouse gas emissions and any other environmental impact related. Compliance with ISO requirement is used as a certification of an organization’s energy management system. It does not establish absolute requirements for energy performance beyond the commitments in the energy policy of the organization and its obligation to comply with applicable legal requirements and other market based requirements. In the framework of ISO 50001, the identification of the variables affecting energy performance and the selection of the parameters that can be monitored and influenced by the organization need to be documented, reported, verified and included at the energy management system. Design and procurement practices for equipment, systems, processes and personnel that contribute to energy performance should be applied according the ISO 50001 standards.

This International Standard is applicable to any organization wishing to ensure that it conforms to its stated energy policy and wishing to demonstrate this to others, such conformity being confirmed either by means of self-evaluation and self-declaration of conformity, or by certification of the energy management system by an external organization (ISO, Energy Management, 2011).

3. ISO 19030-Ships and Marine Technology -Measurement of changes in hull and propeller performance

This standard guideline focuses on the measurement of ship’s parameters and on their contribution to the performance of the subject vessel. Hull and propeller performance, which will be the subject of this study, refers to the relationship between the condition of a ship’s underwater hull and propeller and the power required to move the vessel through water at any required given speed. Measurement of changes of the performance of a specific vessel over time makes it possible to indicate the impact of its current condition and supports maintenance decisions, such as hull cleaning and propeller polishing, or repair and retrofit activities.

The goal of this standard is to prescribe and define practical methods for measuring changes of a specific hull and propeller performance and set of relevant performance indicators. The three parts of this ISO standard are:

- Outline general principles for the measurements of change in hull and propeller performance and define a set of indicators, which support company's decision on the mentioned matter;
- Define the default method of measuring changes in performance and calculating the set indicators. It also provides guidance on the expected accuracy of each performance indicator;
- Outline alternatives to the default method and the result of such in overall accuracy and applicability of the standards.

The general principles and methods that a monitoring system, certified with ISO 19030 should follow covers a variety of requirements addressing measurement equipment, handling of information, procedures and methodologies which are generally available and recognized internationally in shipping industry.

C. Other requirements

Another very crucial requirement for tanker vessels, like the VLCC tanker used for the current thesis, is the Tanker Management and Self-Assessment (TMSA), which was introduced by the Oil Companies International Marine Forum (OCIMF). Compliance with its high standards on safety and environmental management is of great importance for management companies and operators in order to be attractive to major charterers. The latest revision of TMSA, TMSA 3, refers to Environmental and Energy Management at the element 10. TMSA is divided into four stages of compliance, which are the indicators of the overall self-assessment procedures. The stages of element 10 are described below (OCIMF, 2017):

The first stage requires the identification of all sources of marine and atmospheric emissions attributable to the company and vessel's activities and the procedures followed to minimize emissions by controlling their sources and ensure that they are always within permitted levels as per the international regulations (IMO).

The second stage requires the monitoring of key parameters, which could be the overall daily fuel oil consumption, speed, condition of the vessel, trim and the weather condition the ship faces. For the second stage, a voyage by voyage basis is enough for compliance. For the selected parameters, a procedure which establishes baselines and measures used to improve the environmental performance, monitoring and evaluation procedures should be included at the vessel's environmental management plan.

In order to comply with the third stage of the element 10 of TMSA, specific emission reduction targets are set, after the evaluation of their impact to the environment. Performance improvement on the building process are also taken into account for this stage. Hull optimization, use of energy saving devices and upgrade of the equipment (e.g. LED lights, variable frequency drives on heavy power consumers) are evaluated.

For the fourth and stricter stage, a demonstration of used technology to enhance energy efficiency is required. These technologies include major modifications or upgrades at the design stage, which could include emerging coating technologies, upgrade on the machinery equipment, waste energy recovery systems or a better engine design and optimization on the operational condition of the vessel (de-rate of main engine), or the use of alternative energy efficient fuel are taken into account. Equipment used to increase the hydrodynamic performance (ducts, bulb rudders, pre-swirl stators, propeller boss cap fins, etc.), are also included as measures to improve the environmental performance of the vessel. Another aspect of this stage of compliance, is the real time performance monitoring and comparative analysis of the ship and the periodical evaluation and benchmarking of it, as well as the evaluation of the technologies used and applied to the vessel. Measures to achieve and evaluate the environmental and energy efficiency goals, defined by the company are crucial for a compliance of this stage. The most important part of compliance of this stage is to quantify and deliver an estimation of the impact of the technologies used, in achieving the set goals.

D. Performance Monitoring and Analysis Systems

In order to fulfill the market trend in monitoring and analysis of ship's performance, a number of systems of variable complexity and matureness have been developed, signifying an attempt to address the loosely defined problem of ship performance. In this chapter a review of the problem's parameters and the types and characteristics of different systems is given, with the aim to ascertain the required set of data and the required improvement in the collection and processing of them, towards an advanced performance monitoring and analysis system (PMA).

The scope of performance monitoring systems is to provide assistance to the operator and the involved stakeholders (e.g. charterers), in order to understand and evaluate, in any given period, the capabilities of the vessel in terms of speed range she can obtain, the respective power needed, the corresponding fuel consumption, as well as ship's behaviour in any foreseen state of loading and weather conditions. These aspects can benefit operators to reach a more economical operation and increase the available information for all involved stakeholders, leading to correct business decisions and developments. Knowing and managing fuel efficiency, documenting efforts, and quantifying improvements is part of what running a performance monitoring and analysis system have to cover. Investigating the benefits of dry docking or hull cleaning, propeller polishing as well as retrofits in some cases, quantifying efficiency of paint system (and paint application) is also part of the outcome.

When the capabilities of the vessel are known and the performance of the vessel is evaluated at different stages of its life and in different conditions, the quality of any investment, like anti-fouling paints, modifications or the effect of maintenance events (hull cleaning, propeller polish, dry dock) can be assessed. The economically optimum interval, or the condition in which a maintenance event is beneficial, can be defined and the economic penalties and delays can be identified and evaluated in order to improve voyage planning and management of the vessel by the assessment of hull condition.

If all performance affecting parameters are measured simultaneously at frequent intervals, a large database becomes available which can be used to design an optimization system. Trim, draft, autopilot and engine settings in different environmental conditions are examples of areas that can be optimized (Hasselaar, 2010). Moreover, with the availability of an accurate speed-power demand curve that represents the actual capabilities of a vessel, the most optimum service speed can be determined based on the total expenditure. Also, with the availability of prompt and reliable information of the vessel's sailing performance, the ship's crew would be able to obtain an immediate understanding of the impact of their actions.

As a response to regulations and global pressures caused by environmental concerns on ship operators, classification societies have introduced notations (green certificates) concerning ship efficiency and pollution reduction on the design stage, which certify that the vessel's design and equipment are eco-friendly and give a competitive market advantage (e.g. 'Environmental Passport for Design (EP-D)' (DNVGL, 2018)). Shipbuilders deliver their newly built vessels following their trials on the basis of calm water and reference is therefore often made to empirical correction factors to include service conditions. The availability of a continuous performance monitoring system allows better assessment and evaluation of emissions and environmental impact, and helps in obtaining an environmental notation. The introduction of CO2 indexing schemes described in previous chapter (EEOI or other indicators) for ships also require continuous monitoring to accurately index a ship on a scale.

Continuous performance monitoring and assessing of ship's condition, is a very valuable input in order to have an accurate charter party description, as the performance of the vessel is not the same over its life cycle and adjustments should be made in order to avoid conflicts with the charterer and minimize performance and speed claims. The speed and fuel consumption warranties in charter party agreements are imprecise in engineering terms and reflect the evidential difficulties that arise in dispute when it is not known whether inefficient ship performance is caused by adverse weather conditions or a poorly maintained vessel. When the ship's capabilities and ship performance can be determined irrespective of environmental or loading conditions and with higher precision, agreements can be defined more precisely (Hasselaar, 2010).

In the current framework, described above, the aim of this thesis is to investigate the feasibility of developing a detailed ship performance monitoring and analysis system for typical merchant ships, in our case a VLCC tanker in order to assess ship performance. The ultimate goal of such a system, would be to provide an assessment and evaluation of hull and propeller condition and aid in the reduction of power needed for the propulsion of the vessel, by proper maintenance. Monitoring power demand of the vessel is linked with a positive impact on the fuel oil consumption as well as environmental pollutants of ships. Within this framework, the specific objectives of this thesis are to:

• review the state of art of performance monitoring and analysis

• identify factors that influence ship performance

• develop a methodology to convert performance to 'standard' conditions

• evaluate the developed system and the conclusions made by the methodology used

The elements in which the model is based will be presented briefly below and discussed in detail in following chapters.

1. Ship's Resistance

A ship's resistance is influenced by a variety of factors. The problem of moving the ship over water either in good or bad weather conditions involves the proportions and shape or form of the hull, the size and type of propulsion plant, and the system to transform this power to effective thrust. Power delivered to the shaft and then to vessel's propeller is used to overcome ship's total resistance produced by its relative movement through water and air, and result in maintaining a requested speed.

Total resistance consists of many sources-resistances, which can be divided into categories (Lewis, 1988).

A streamlined body moving in a straight horizontal line at a constant speed, deeply immersed in an unlimited fluid, presents the simplest case of resistance. Since there is no free surface effect, there is no wave formation and therefore no wave-making resistance.

For a non-ideal fluid, pressure differences will be created through the length of the vessel, with high pressures observed at the forward part and lower pressure at the back, inducing an opposing force in the direction of movement.

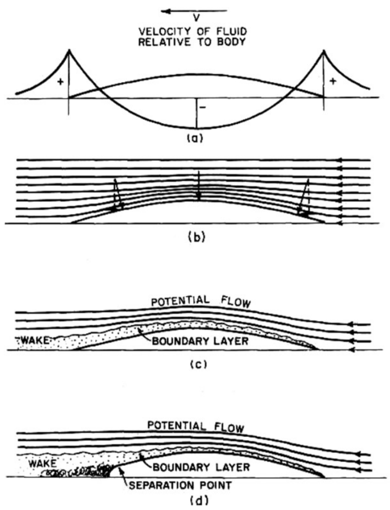


Figure I-5 Flow around a submerged body (Lewis, 1988)

Another source that creates resistance is that vessels sail on the free surface of the water. Moving on the free surface creates a wave field. The energy contained and the energy needed to maintain such wave field is provided by the vessel propulsion power. This force is known as wave making resistance (Politis & Tzabiras, Ship Resistance and Propulsion (in Greek)). The resulting resistance corresponds to the drain of energy into the wave system, which spreads out astern of the ship and has to be continuously recreated. Wave resistance is lower for low speeds and increases at high speeds. In principle, it defines a speed barrier, so that further increase in ship's propulsion power is converted and consumed by the waves generated. Normally, represents 8-25% of total resistance for low-speed ships.

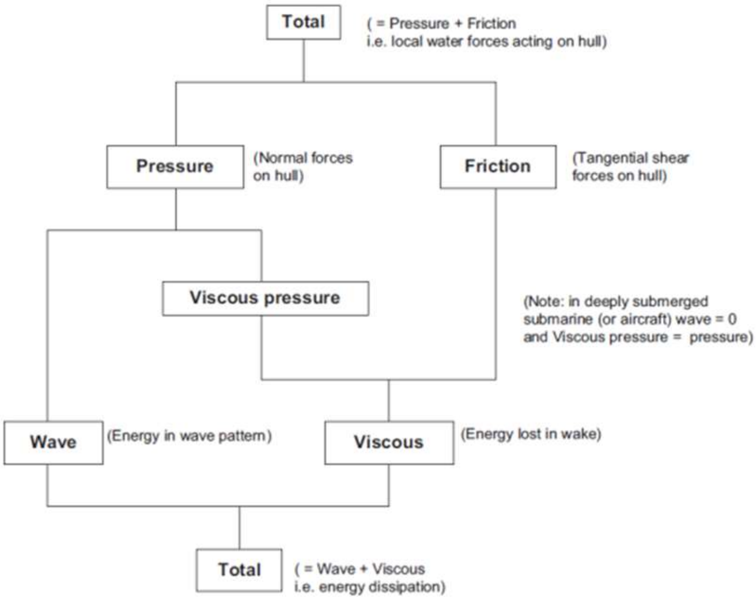


Figure I-6 : Resistance components (F.Molland, 2017)

During the operation, the condition of the ship differs from the calm water and clean hull condition in which the above analysis is applicable. Marine organisms and barnacles will grow on the surface of the hull, which means that the vessel no longer has a smooth surface. In addition, performance of the vessel can be influenced by shallow water, adverse currents, strong wind, as well as sea conditions, wave amplitude and frequency, that could have a great impact in the overall performance.

Frictional resistance increases over time, as fouling and initial roughness increases. An attempt to limit this factor of resistance is made by the use of anti-fouling hull paints to prevent marine organisms' attachment on the hull and slow down their growth. This component, is of great importance, as frictional resistance represents a considerable part (often equal to 70-90%) of total resistance for low-speed ships with blunt shape such as bulk carriers and tankers (MAN, 2016).

Paints containing TBT (tributyl tin) as their principal biocide, which dominated a big market share of the seagoing merchant vessels, have been banned as toxic. This decision made by IMO (IMO, Anti-fouling Systems, 2002), pushed to other alternative solution as copper or iron based paint, or silicon-silyl acrylate paints.

Weather effect, can be described by two main sources of resistance.

Added wave resistance is the element of resistance linked to the vessel sailing in a seaway, related with the action of waves on the hull as well as with the induced ship motions. Waves can be distinguished in wind generated and gravity waves and swells. Wave characteristics are affected by a variety of factors, as wind speed and duration, water depth, currents etc. Waves appear in an irregular form and their characteristics are usually described by a wave energy spectrum, which is time- and space-dependent (Mandel, 1989). A ship's motions and accelerations as well as its propulsion power requirements are dependent on its hydrodynamic characteristics at the given loading condition and the actual environmental conditions at the given time and area of operation.

Waves approaching a vessel can cause significant increase of the added resistance, firstly by the diffraction effect of the hull on the encountered waves and secondly, from the indirect effect of the pitching, heaving and rolling motions caused by the waves. As an aftereffect, the required rudder action, in order to correct vessel's course may contribute to a further increase (Mandel, 1989).

Diffraction resistance is dominant in wave regions where the waves are short compared to vessel length. On the other hand, motion related resistance, is the primary component of wave added resistance caused by wave lengths comparable to the vessel's length. For longer waves, it is observed that the vessel responds by following the wave motion and limiting the related resistance factor.

Wind Resistance, depends upon the vessel's apparent speed and upon the area and the shape of the upper body, exposed to wind forces (Lewis, 1988).

Even a ship sailing in calm weather (no incident waves or wind) experiences an air resistance component due to its speed. Wind blowing at any given condition, combined with vessel's speed over the ground, produce the relative wind speed and direction that an observer onboard the ship can experience. The true wind, is termed to be the wind which is generated due to natural causes and exists at a point above sea, without the interaction to any object, in our case the vessel. The relative or apparent wind is the vectorial summation of the velocities of the true wind and the vessel's speed over ground. Relative wind generates a force which is usually called air resistance and it varies according to the vessel's speed and shape of the above water part. Wind resistance is primarily linked to the force over the transverse area of the vessel and on eddy-making phenomena that produce a pressure difference over the object (Lewis, 1988; A.F. Molland, 2003).

Shallow water effect can be divided into two parts. The first is an increase in the resistance of the vessel, due to the increased velocity of the surrounding water, resulting in an addition sinkage of the hull and thereby an increase of the wetted surface, which leads to additional frictional resistance. The second element of shallow water effect, is that in limited water depth, the ship-generated wave pattern changes, which in turn results in a wave resistance modification.

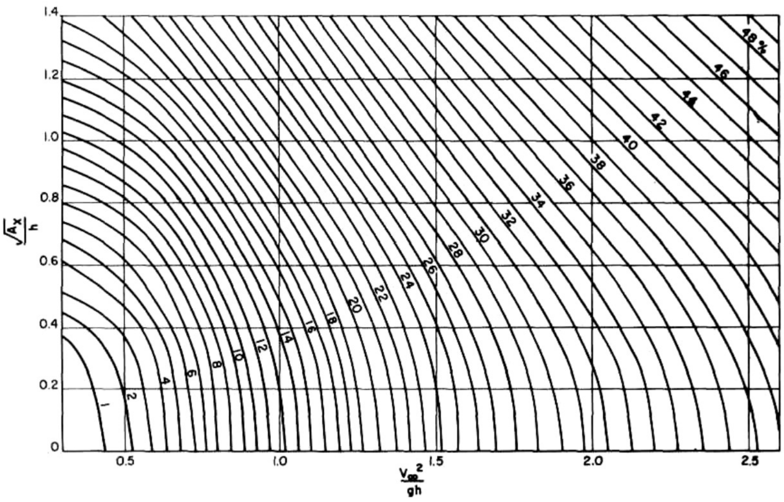


Figure I-7: Schlichting's chart for calculating reduction in speed in shallow water (Lewis, 1988)

Trim effect, owing to the change in pressure distribution around the hull, dependent on the condition of operating and speed of the vessel. At low speeds the increased draft aft makes the stern virtually fuller, with a consequent increase in form and separation resistance, whereas at high speeds this is more than offset by the reduction in wave-making due to the finer entrance in the trimmed condition (Lewis, 1988; Mandel, 1989). However, trim effect cannot be defined accurately and the resistance link to it is a difficult problem to solve.

Resistance due to steering, indicates the resistance contribution of the drag and lift force due to rudder angle. Rudder is acting as a foil at ship's wake, creating pressure differences between sides. The total resistance due to the rudder consists of the drag of the rudder itself plus the extra drag that the rudder creates when it is turned (Aas-Hansen, 2010).

Sea currents, are a result of many environmental, geographical and physical parameters. Especially in coastal areas, current speed and direction may vary considerably with depth and depend on tidal and global currents, wind and wave condition over a period of time. The variations in current depending on the distance from the sea surface make the definition of the mean current, the ship's underwater hull experiences difficult (Hasselaar, 2010). A speed log installed at the bottom of a ship, measuring the speed of the water relative to the bottom of the hull, indicate the actual speed experienced by the ship. Often more than one speed logs are recommended, to be placed at different positions to avoid and easily spot any log malfunctions.

2. Propulsion

Typically, in early stages of the design process, propeller and vessel's hull are treated separately, however the interaction of those two elements is of great importance to understand and evaluate the relevant characteristics and interaction effects. For a given propeller with known sectional characteristics, performance and efficiency can be evaluated by engineering tools, by calculating thrust, torque and induced velocities at points on the lifting line, as well as lift and drag forces.

While the hull is towed or advancing, an area of high pressure over the stern is formed, which has a resultant forward component reducing resistance. However, on a self-propelled vessel, the pressure over that area is reduced by the action of the rotating propeller, accelerating the water inflow, and simultaneously reducing pressure, which results on the reduction of the forward component and an increase of the resistance. Thus, the thrust needed to propel the vessel is greater the thrust measured at the resistance test. This loss of thrust, expressed as a fraction of the bare hull resistance over the needed thrust to advance, is called thrust deduction factor.

Typically, the propeller is located behind the ship, thus, the hull shape influences the flow towards the propeller. The propeller is working in water, which has been disturbed by the presence of the hull and the shape of the stern, which in general, has acquired a forward motion in the same direction as the ship. The frictional drag of the hull causes a following current, which increases in velocity towards the stern and produces a wake having a considerable forward velocity relative to the surrounding water, dependent mainly on the roughness of the surface, the area where friction is developed and the relative speed of the vessel to the water surrounding it. Also, the streamline flow, past the hull, causes an increase of pressure around the stern, where the streamlines are closing in and leading to the propeller, according to Bernoulli's law. When propeller is running, the rotation and the developed thrust of the propeller, accelerates the water ahead of it and as a result lowers the pressure even more and increases the velocity around the stern. Both effects, augment the resistance of the ship above the towing resistance of the bare hull. The velocity field generated is called the wake, and the result of it, is that the propeller is not advancing relatively to the water at the same speed as the ship, but at some lower speed depending on the wake field. The speed in which the propeller is advancing, is called advance speed. Difference between the uniform inflow velocity field of the propeller operating in open water from the field experienced by the propeller due to the presence of the hull and its rotation, leads to a variation of the propeller efficiencies. Additional components, which influence the propeller, are the vessel's wave system and the wave system of the sea, which alter the velocities in the propeller plane

Modelling of flow around a marine propeller's unsteady free wake motion has been formulated by (Politis G. K., 2003). Effective wake is an important parameter to determine the required power, but the corresponding effective wake field cannot be directly measured. Computational approaches considering the ship and the working propeller interaction are in theory able to compute the influence of the propeller on the wake, but it is difficult to separate the inflow on the propeller, the induced velocities and their interaction.

3. Data Acquisition

After describing the more important parameters influencing a ship's performance, a review of the input needed and the data collection methods are presented at the current chapter. Accurate data and a robust data acquisition and transmission system is the pillar of a functional performance system.

For a number of parameters, the limitation regarding accuracy is determined by the characteristics of the sensors, or the tools used to calculate them by the environmental conditions and in many case of the implementation method and the way of calibration.

Commonly, readings are averaged over a time frame in order to be easy to handle and use for the performance analysis.

Data collection methods can be separated in two main categories; manual input and automatic collection using sensors and other sources of data. In order to comply with ISO standards 19030-part 2 explained above, automatic collection is needed as the minimum data acquisition rates cannot be attained by manual input, as shown in the table below.

	Parameter	**Minimum data acquisition rate**
Primary parameters	Speed through water	every 15 seconds (0.07 Hz)
	Delivered power	every 15 seconds (0.07 Hz)
Secondary parameters	Shaft revolutions	every 15 seconds (0.07 Hz)
	Relative wind speed and direction	every 15 seconds (0.07 Hz)
	Speed over ground and ship heading	every 15 seconds (0.07 Hz)
	Rudder angle	every 15 seconds (0.07 Hz)
	Water depth	every 15 seconds (0.07 Hz)
	Static draught fore and aft	Whenever loading condition changes
	Water temprature	every 15 seconds (0.07 Hz)

Table I-2 : ISO 19030-2-Minimum data acquisition rate (ISO, Ships and marine technology-Measurement of changes in hull and propeller performance, 2016)

a) Manual data logging

Every merchant vessel is required to keep a daily logbook to monitor fuel consumption, engine performance, navigation and loading condition as well as other important parameters. Engine and deck logbooks are traditionally filled once a day or on a 4 hours' interval (every watch) and reported to onshore management every day in noon report, as an average of the day. The number of variables logged, depends on the requirements and policy of the shipping company and the capabilities of system used. A typical form of telegram-noon report can be seen below, with the main parameters reported (distance covered, speed, shaft revolution per minute, delivered power, weather conditions, fuel consumption etc.).

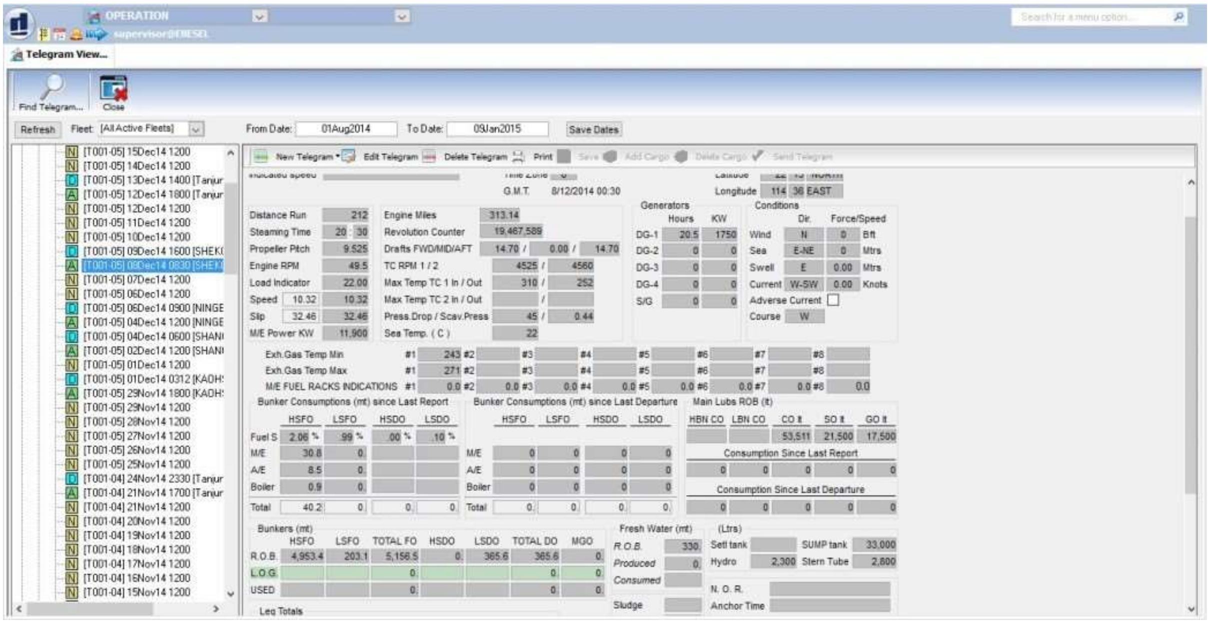


Figure I-8 : Typical Telegram Report Form (DANAOS, 2018)

Often, logbooks and noon reporting are used for performance monitoring due to the fact that they are already implemented for reporting to the onshore personnel and management and the continuous update of vessel's records. As a result, by the use of these data, there is no extra cost for data acquisition for the company. However, performance monitoring requires a higher level of accuracy and a higher frequency interval than abstract logbooks can provide. The sources of inaccuracy of the manual data logging method, as noted by (Hasselaar, 2010) could be:

- Uncertainty in the used instrumentation. In order to avoid the impact of a bad calibrated instrument, critical monitoring equipment is often duplicated and crew states from which source data is acquired and define any source of variation between them.
- Wrong data collection protocol. A time lag of the local time of the vessel and the UTC time used from onshore personnel in order to evaluate performance is causing differences in data synchronization.
- Insufficient training. For the parameters reported from visual observations, e.g. weather condition, inaccuracies due to human element cause inconsistencies.
- Inaccurate data collection. Certain parameters must be averaged to be reported. Wrong averaging, spot measures and even big variation in these parameters through the day (period of reporting) could result in a poor data collection.
- Limited logging frequency. Workload of officers on duty limits the careful monitoring of parameters reported.
- Errors in data entry. Experience indicates that abstract logbooks contain data inconsistencies and unrealistic parameters report

Using manual data logging, may include uncertainties and limited data recording, but it is based on already known procedures and instruments. It requires minimum investment in devices and measuring tools as well as limited training of crew and onshore personnel, as they are already familiar with the procedures of reporting. These characteristics, make manual data logging and the respective performance systems easy to implement and attractive to a low cost philosophy.

b) Automatic data logging

On the other hand, with the introduction of wireless data transmission and the development in satellite communication, data could be transferred to office electronically and automatically without any involvement of the crew. A data acquisition system interconnected to all necessary devices can store and transfer all monitored parameters to office. A fair implementation of such a system could contribute significantly to the improvement of data quality and frequency and potentially comply with ISO 19030. A combination of different data sources is often necessary and should be carefully implemented in order to avoid mismatch of the set of data.

Continuous monitoring allows signal validation, filtering and averaging for increased accuracy and reliability.

Uncertainty and errors in data entry are described and documented by sensors characteristics.

Malfunction of sensors could be spotted by onshore personnel designated to the PMA system.

Automatic data collection allows real time analysis and feedback on vessel operation.

Upgrading of vessel's voyage storage recorders or equipment with similar technology and in deep investigation on the transmission systems could result in a continuous and accurate history representation of parameters, which will be used for the performance monitoring and analysis system.

This kind of implementation, requires in most cases a fair investment in high quality measuring devices, as well as, data acquisition and transmission systems. Maintenance procedures and training of personnel is essential to reassure the continuous and accurate measurements.

Over the past years, many advances have been made in data collection systems, utilizing automatic data acquisition systems for on-board and ashore analysis. However, since most commercial PM&A systems are black boxes, whereby the operator or the management company cannot get full insight in how data is collected, conditioned or analysed, it is difficult to comment on their characteristics and algorithms, resulting in many cases in questioning the reliability of their key performance indicators (KPIs). Thus, many shipping companies use, in many cases additionally, their own methodologies for data collection and performance monitoring.

4. Performance analysis methods

A variety of published methods for performance analysis are used or developed for shipping. Most of the performance monitoring system products in the market use a combination of them in order to do the analysis. Their goal is to determine a methodology to convert data received by a variety of sensors and other sources to a standard condition, in which evaluation is feasible. However, they can be divided in the following categories, based on the main method used to perform such analysis:

- Methods using regression & trend analysis over time.

Long-term analysis by deriving trends is a simple approach to performance monitoring, but efficient in identifying changes over time. These models can be implemented without requiring in-depth knowledge of the hydrodynamic characteristics of the vessel which in some cases is difficult to acquire. The assumption is that these characteristics could be ignored, if we apply proper grouping and filtering, in a long term analysis. Trend analysis, however, relies on the availability of large amount of high quality data collected consistently. The main problem of this kind of analysis, is the high scatter of points, caused by varying environmental conditions and changes in parameters not taken into account, such as small differences in draft. This problem results in high uncertainty margins and could affect decision making in extent.

Example of such a system is BMT^{SMART}, which uses trend analysis on monitored parameters forming KPIs for supporting management and maintenance decisions in respect to vessels' main particulars and physical models (Sea Trial).

> "*Fleet & Vessel Performance Management (FVPM) solutions provide sophisticated data collection, data display and data analysis services to support optimal decision-making that helps ship owners and operators to better manage the performance of fleets and vessels. This is achieved through a simple four-step approach: Measure, Manage, Analyse, Action."* (BMT, 2018)

- Statistical methods using techniques to account for parameters variation

The accuracy of these methods depend on the suitability and efficiency of the statistical model used. The advantage of a complex statistical model is that it can produce results without an extended physical baseline, based on experimental data, which may be difficult or expensive to obtain. However, the risk of a system which fails to represent reality is high. Also, ignoring the physical mechanisms of related physical phenomena affects in some extend the quality of the outcome.

Marorka is an operational data collection system-application, which identifies variations of the input parameters over a period. Sampling period is crucial in order to define valid reference lines and in most cases it is suggested to have an approximate 6 months of data collection prior delivering any analysis.

"Data management includes powerful analysis tools. These are used for graphically trending and comparing real-time operational values over a period of time. As a result, the crew can locate focus areas for improving energy efficiency and for saving fuel." (Marorka, 2018)

- Sophisticated algorithms and machine learning tools.

This method, successfully implemented already in a variety of industry sectors, has entered now the shipping sector. The variety and complexity (many of them with non-linear characteristics) of the physical problems an in deep performance analysis faces, is a difficult task to solve for any system. Companies that provide systems using sophisticated algorithms and machine learning claim that with an accurate setup and the use of the physical background of the problem, they could estimate with satisfactory accuracy a vessel's performance. However, the setup of the different problems, as well as the dependence of these problems on factors affecting various resistance components and the connection between such factors are a difficult task for any software engineering company, specialized in marine energy management. While these type of systems are still immature, it is a state of the art technique with a high possibility for improvement in the years to come.

Such a system, which was originally developed for cruise ships and now has widen its market range is Eniram. Eniram's first product was oriented towards trim optimization of cruise ships and the estimation of various loads.

> *"We use the advanced mathematical models in the Eniram Insight Factory to create insights for each vessel – for example, how to achieve optimal trim to save fuel, exact RPMs to reach port just-in-time, or when to schedule a hull cleaning." (Eniram, 2018)*

- Deterministic performance analysis

Performance analysis by using hydrodynamic characteristics and deterministic solutions to physical problems, accounting for changes in environmental and operational conditions was introduced many years ago. Assessing performance by this way requires a large set of experimental data and hydrodynamic calculations, in order to cover and estimate the performance of the vessel in the variable environment in which it will operate. Tests in this extend are very rare to be found in the environment of a shipping company. Negative aspects of this method are the high cost and computational power demand, as well as that it is time consuming. As a result, very few companies could perform an analysis using this method.

An example of such a system based on extended sea trials, model tests, auto-propulsion tests, propeller open-water experiments and various advanced computational fluid dynamics calculations is the Maersk Ship Performance System (MSPS), a product of the former Maesrk Maritime Technology (MMT), now part of Maersk Fluid Technology, which is intended only for the internal use of Maersk group of companies.

Another system of this philosophy, is Hellintec's Ship Efficiency Monitoring Toolkit (SEMT). SEMT is a Ship Specific performance tool, based on a model specifically prepared for every ship. The preparation of the system requires engineering information, depending on the applicable modules such as detailed hull model, including characteristics such as transom, bulb, superstructures and rudder details, propeller geometry and its characteristics (non-dimensional thrust and torque curves versus the advance ratio), main engine details and operational data from the engine manufacturers' shop test results, ship specific model tank tests results and sea trial results.

> *"SEMT is a software package designed to assist Ship Operators monitor and optimize the Performance, Fuel Consumption and Greenhouse Gas Emissions of vessels." (Hellintec, 2018)*

To sum up, there are a lot of systems available in the market using several approaches, with each one of them resulting to different accuracy and procurement cost. The basic principles and data collection differ. For advanced systems, automatic logging and evaluation of data is required. Proper filtering and grouping of results is a crucial stage of the implementation of any system. Validation of data, evaluation and follow up of any performance index chosen for the monitoring of changes over time, will help to identify the contributing parameters of any deviation.

Balancing cost, accuracy and evaluating investment needed per system is a multivariable problem affecting system selection and business decisions.

II. Neural Networks

A. Overview

Today's computers have increased dramatically their capabilities. They can perform complicated and enormous amount of calculations, handle vast data sets and complex control tasks. However, till recently, there were classes of problems which could not be processed by the computers, but for which the solution could be easily found by the human brain. The computational power needed to solve these problems made this computing option inefficient and in most cases, logical assumptions were made in order to estimate sufficiently, via an analytic equation. Examples of problems that a human brain can process much more efficiently than the computers, are character recognition, image interpretation or text reading. These kinds of problems have in common that it is difficult to derive a suitable algorithm to fit them perfectly. Unlike computers, the human brain can adapt to new situations and enhance its knowledge by learning. It is capable to deal with incorrect or incomplete information and still reach a satisfying result. This is possible through adaption and logical simplification of the problem, while evolving or learning new abilities (Smith, 1997).

A relatively new approach to address these classes of problems is the fast growing machine learning concept. Artificial Neural Networks (ANN), as one specific category of this group of approaches, are simplified models of the central nervous system of the human brain and consist of intense interconnected neural processing elements. They are inspired by the function of human brain and its way of processing information. The model of the neural processing elements is nerve cells. A human brain consists of about 10^{11} of them. All functions are carried out in a parallel-distributed way, by non-linear processing units connected between them, called neurons.

The development of artificial neural networks began approximately 70 years ago but early successes were overshadowed by rapid progress in computing. The first milestone, was the work of Warren McCulloch and Walter Pitts, who created a computational model for neural networks based on mathematics and algorithms called threshold logic (Pitts, 1943). This model paved the way for neural network research to split into two approaches. One approach focused on biological processes in the brain while the other focused on the application of neural networks to artificial intelligence. However, claims made for capabilities of early models of neural networks started casting doubts on the entire field and slowed down the research on that field. One of the first complete, but still immature application of the hierarchical object recognition system, which belongs in the area of machine learning mentality, was Neocognitron by (Fukushima, 1980). This application was oriented to recognizing stimulus patterns based on the geometrical similarity of their shapes without affecting their positions. Recent renewed interest in neural networks can be attributed to several factors. Training techniques have been developed for the more sophisticated network architectures that are able to overcome the shortcomings of the early, simple neural networks, which could not perform on a complex multi variable non-linear problem. High-speed digital computers make the simulation of neural processes feasible. Technology is now available to produce fairly strong and specialized hardware equipment, which could address the demand of computational power to support neural networks. Access to huge data bases and the need to monitor numerous parameters on any scientific field or industrial application, made clear that a need for an approach that could process this vast amount of information is needed in order to advance in the forthcoming years. The promising future of machine learning application, attracted the interest of computer scientists and engineers around the globe. Colossal companies, like Google, started investing in such projects. Simple examples of such applications using Artificial Intelligence, are text recognition as a feature of Google Translate or Apple's "Siri" voice search. In this framework, this thesis focuses on a "data analysis" approach of modelling complex, non-linear problems linked to vessel performance and the estimation of the power needed to propel a ship in in-service condition, taking into consideration its' loading, service and weather condition.

B. Artificial Neural Network architecture and philosophy

As mentioned above, Artificial Neural Network (ANN) are computing systems vaguely inspired by the interconnected neurons of the biological neural networks, arranged in layers communicating with each other through neural synapses, which "learn" to perform tasks by considering observed examples and input parameters with unknown impact in the final output. The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network's components in order to attain the desired design objective. To achieve good performance, neural networks employs massive interconnection of simple computing cells referred to as "neurons" or processing units (Haykin, 1999). Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. Each connection between artificial neurons is called "edge". Typically, the artificial neurons and edges are linked to a weight that adjusts their impact as the learning process proceeds.

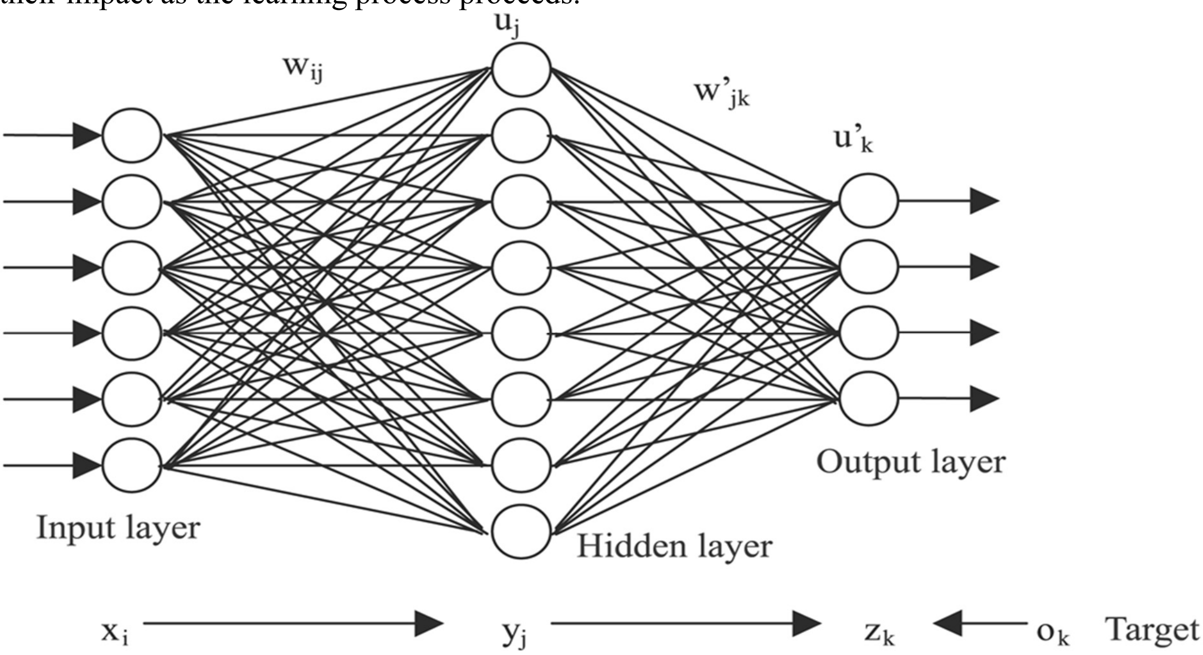


Figure II-1 Artificial Neural Network – Architecture of a multi-layer perceptron

Based on the arrangement of neurons and layers created, an Artificial Neural Network could be characterized as single-layer or multi-layer network. The first type of networks contains only one layer of neurons as its output layer, while the second has "hidden" layers between the input and the output layer, not visible to the end user. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers' multiple times. With respect to the kind of their neural synapses, networks may be characterized as feed-forward or recurrent. The data in feed-forward networks flow in only one direction, starting from the input layer and continue through the network to the final, output layer. In feed-forward networks, as the one demonstrated at Figure II-1, the neurons or nodes are organized in layers. Connections are only allowed between neurons of different layers directed towards the network's output layer. Connections between neurons of the same layer or in the opposite direction than the one described is prohibited. However, the developer has the option to contain connection only to neighbouring layers (first order networks) or to define and permit connections between all layers, in respect to the limitation the feed-forward network has. The first layer of the network is the input layer, which is constructed according to the data input form. This layer does not include neurons with processing ability. It only forwards the inputs to other neurons (u_j). The output layer, is the last layer and provides the final output of the network. Layers in between are called hidden, because they are not "visible" to the end user. Recurrent networks give the option to the developer to perform at least one feedback interconnection, which links the output of a neuron, or a group of them, with the input of another neuron, placed in the same or in the previous layer (Haykin, 1999). In many cases, the organization into layers is completely dropped. For example, a recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. The presence of feedback loops has a profound impact on the learning capability of the network and on its performance. Moreover, the feedback loops involve the use of particular branches composed of unit-delay elements which result in a nonlinear dynamical behaviour, assuming that the neural network contains nonlinear units. Each neuron connection or "edge" is done by directed communication links, which includes an associated weight (w_{ij}) to each input signal. The weights represent the information and the magnitude of it used in any given processing unit – neuron. Each neuron has an internal state, called activation or activity level, which is a function of the inputs it receives. In the common format and neural network architectures every neuron broadcasts its output signal to several other neurons. However, different transfer functions could be applied to each layer connection.
The equation representing the processing ability of each neuron is shown below.

$$\boldsymbol{a_j^i = g(\sum \Theta_{ik}^j \cdot x_{ik})}$$ *Equation II-1*

Where,

a_j^i , is the "activation" of unit i, in layer j

Θ_{ik}^j , is the matrix of weights controlling function mapping from layer j to layer $j+1$, of the unit i placed in any layer k

x_{ik}, is the signal input of the input unit i placed in any layer k

And g is the activation function of the layer or the processing unit (i.e. sigmoid, linear etc)

As a result, it is easy to conclude that if a network has s_j units in layer j and s_{j+1} units in layer j+1, then Θ^j will be dimensioned as $s_{j+1}\times(s_j(+1))$, where +1 is added if we add a bias at the input signal

There are three main categories of transfer functions commonly used. The simplest of them is linear. By using linear transfer function, the neuron's input is a linear function of the weighted input parameters-signals. Linear transfer function is commonly used for the transmission of the signal of the output layer. The simple graphic representation of this kind of transfer function is:

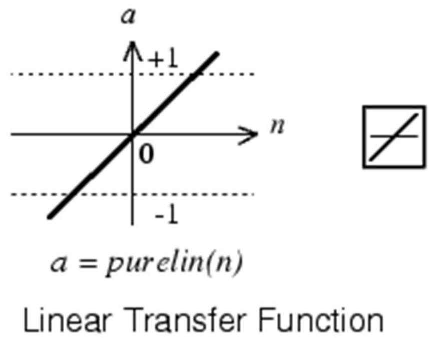


Figure II-2 Linear transfer function (MathWorks, Matlab toolbox, 2018)

An alternative approach is the use of binary functions and limits (also known as hard limit function). At this category the network generates a threshold, where, when signals fail to pass, these signals are discarded and not taken into account at the processing stage or given significantly different "weight".

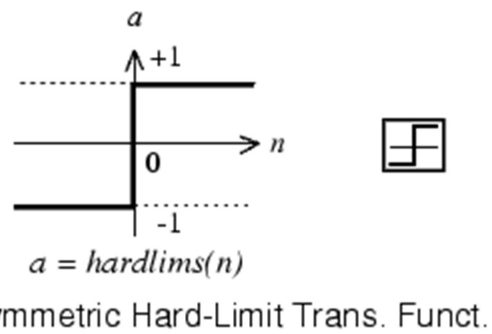


Figure II-3, Hard limit (MathWorks, Matlab toolbox, 2018)

Last category is the sigmoid functions. Functions included in this category are continuous, differentiable monotone and usually set by default (or the user) in the range of [0; 1] or [-1; 1] domain. Examples of functions of this category are, sigmoid (tan sigmoid) function, logistic sigmoid function and Elliot sigmoid. The equations of these functions are given below:

Tan-Sigmoid Transfer function $\boldsymbol{y_k = \frac{2}{1+e^{-\lambda u_k}} - 1}$ *Equation II-2*

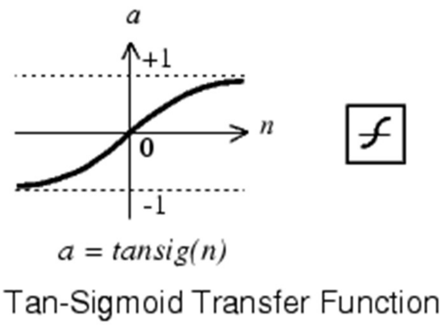


Figure II-4, Tan-Sigmoid Transfer function (MathWorks, Matlab toolbox, 2018)

Log-Sigmoid Transfer function $\boldsymbol{y_k} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e^{-\lambda u_k}}}$ *Equation II-3*

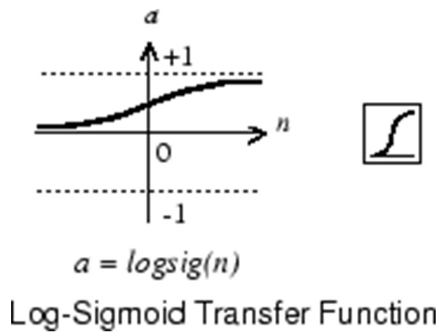


Figure II-5, Log-Sigmoid Transfer Function (MathWorks, Matlab toolbox, 2018)

Elliot sigmoid Transfer function, takes an S-by-Q matrix of S N-element net input column vectors and returns an S-by-Q matrix A of output vectors, where each element of N is squashed from the interval [-inf; inf] to the interval [-1; 1] with an “S-shaped” function (MathWorks, MathWorks Documentation, 2018).Other functions and their graphic representation can be found at (MathWorks, Matlab toolbox, 2018).The innovative and fundamental feature of Artificial Neural Networks is their ability to learn and adjust themselves to the given problem. ANNs derive its computing power through its massive parallel distributed structure and its ability to generalize sufficiently, when the characteristics of the network are well designed and trained effectively. The definition of generalization, which is the ability that make this approach innovative and attractive, refers to the ability of producing reasonable outputs for inputs not encountered during training procedure. These two data processing capabilities make it possible for the neural networks to “solve” complex problems with unknown analytic explanation, by decomposing into a number of relatively simpler tasks, which are distributed through the processing units-neurons. The use of machine learning approach and especially neural networks, offer some useful properties. In back-propagation learning techniques, we typically use an algorithm to compute the synaptic weights based on a set of data-examples. The learning process could be viewed as a fitting problem, considered as a non-linear input-output mapping. This point of view, allows us to evaluate generalization as the effect of a good nonlinear interpolation of the input data, as simplifying this approach is. However, when a networks needs too many input-output examples to define the free parameters and result in an acceptable response, then there is a risk the network “memorized” training data. This becomes a problem when the network is adjusted to follow any change present to the set, even noise, which is a feature of the training data but do not reflect in the underlying function that is to be modelled. This “malfunction” is referred to as overfitting or overtraining. When a network is over trained, it loses the ability to generalize between similar input-output patterns.

The interconnection of nonlinear neurons, would result in a nonlinear approach to any given problem. Thus the non-linearity of the model is distributed through the network's components. Nonlinearity is a highly important property, particularly if the physical mechanism responsible for generation of the input signal is inherently nonlinear.
Each example consists of a unique input signal and its corresponding output. By the use of this set of data, either randomly picked through the data set, or defined by the developer-user, the synaptic weights of the networks are modified as free parameters to minimize a cost function selected, which represents the difference between the desired response and the response of the network produced by the input signal in accordance with an appropriate statistical criterion. Training process is repeated for many examples in the set, for a number of times, until the networks converge to a steady state where there are no further significant changes in the synaptic weights and free parameters. The repeating process of using training examples, reapplied to the network is made by distributing the set in a different random order and evaluate the impact of the reapplied data to the networks characteristics and predicting ability. Thus, the network learns from the examples by constructing an input-output mapping for the given problem. Such an approach brings to mind the study of nonparametric statistical inference, which is a branch of statistics dealing with model-free estimation (Geman, 1992). The term "nonparametric" is used to signify the fact that no a priori assumptions are made on the statistical model for the input data. Based on the used training principle, networks can be divided in three categories; unsupervised, supervised and reinforcement learning. In the unsupervised learning, the networks is trying to classify and find a pattern through the input data, without any external information (Ben Krose, 1996). In supervised learning, the network links a series of input and output pairs in order to generate a function, which connects these parameters. In reinforcement learning approach, the network evaluates and rewards its performance through mapping of input-output data in order to minimize a cost function or a performance indicator (Haykin, 1999).

Neural networks have the capability to adjust their synaptic weights in respect to changes in the surrounding environment. This contributes to ease the adjustment on minor changes in the operating environmental conditions over the initial environment the network was trained with. This property is crucial when operating at a nonstationary statistics environment, while the network has the ability to change its synaptic weights in real time, ensuring the stability of the system and making its performance robust over the nonstationary environment. However, trying to implement this approach by an inexperienced developer-user, could result in an adaptive system with short time constants which may change rapidly and therefore tend to change the responses to disturbances and noise, causing the degradation of system's performance. To use the adaptive property of neural networks, the principal time constants should be long enough to avoid and ignore noise and random disturbances but yet short enough to respond to meaningful changes in the input and environment (Grossberg, 1987).

C. Feed-forward Multi-Layer Perceptron

One of the most common and widely used machine learning tools, used for regression or pattern recognition, in which we focus in the current thesis, is the feed-forward multi-layer perceptron (MLP). The Perceptron concept was introduced and described by Frank Rosenblatt (Rosenblatt, 1958). Back then, training a multi-layer network based on large sets of example and data could not be possible. However, a preparatory discussion and a description on the way perceptron could work and be beneficial, was made. Basic principles and future development were described efficiently, as a result it is fair to say that this approach to model human brain functions is one of the milestones of future development of MLPs and machine learning, in general. Following the definitions given, in feed forward MLPs, data flow in only one direction, starting from the input layer and continue through the network to the final, output layer. MLPs consist of an input layer composed by a number of nodes equal to the number of input parameters, one or more hidden layer(s) and an output layer consisting of a number of nodes equal to the dimensions of the output data. The number of nodes in each hidden layer(s) could be adjusted at the needs of the developer and the given problem. Every node except nodes of the input layer is a neuron with a differentiable activation function that uses an input signal and by processing it, generates an output signal. Although it was known since 1960's that MLPs are not limited to linearly separable problems, a big question remained for many years, which slowed down their development. The weight selection and optimization process was unknown. The question needed to be answered was, how the algorithm could determine the nodes where the error could be attributed to, as well as the process with which the system could determine and evaluate the error at any hidden node and how to train the network to an optimum by altering specific weights of "problematic" nodes.

1. Training principles

A very important parameter to define, that impacts greatly the performance of the constructed-developed Artificial Neural Network, is the selection of the training algorithm, with which the weight of every connection is adjusted to the training set of data. The training of these networks is accomplished by the use of a back-propagation philosophy, which is a supervised learning method, as it is described in previous chapters. The training algorithm is used to train the network to recognize impact of every signal to the output of any processing unit as well as mapping of a certain input to a specified output value. The philosophy of this kind of training consists of two main stages. Firstly, the input signal is transferred through all neurons and layers and the output signal is generated based on that input and the weights as defined, prior inputting the data to the network. When the output of the network is generated, the system performs the evaluation of the network's response. This is done through a cost (or error) function, usually by the use of mean square error (or other), in order to identify the deviation between the actual responses of the network and the desired output target and evaluate network's performance. Then the first stage is finished and the system proceeds to the second stage. At this stage the outcome of the evaluation and the deviation measured are transferred backwards in order to change the synaptic weights accordingly, so that the cost function is decreased. This procedure is repeated until the network reaches the desired performance level (if possible), after n iterations. The optimum value of each individual weight is different for each vector of the training set therefore, an estimation of the true change of the network's correspondence due to the modification of the weights, based on minimizing a given cost function over the entire or the validation training set is calculated.

Considering a neuron j being fed by a set of function signals produced by the previous layer, the induced local field $u_j(n)$ produced by the input of the activation function to this corresponding neuron j is therefore

$$\boldsymbol{u_j^n = \sum_{i=1}^{m} w_{ij}(n) y_i(n)}$$ *Equation II-4*

Where, m is the total number of input signals transmitted to the neuron j, the w_{ij} is the corresponding weight of the i input to the j neuron and $y_i(n)$ is the function signal inserted as input to neuron j, by the corresponding output of the neuron i of the previous layer.

Hence, with the use of this input signal, the function signal $y_j(n)$ of the processing unit-neuron j appearing as output of the neuron at the n iteration is

$$\boldsymbol{y_j^n = \varphi_j(u_j^n)}$$ *Equation II-5*

In each iteration n the any-backpropagation algorithm applies a correction $\Delta w_{ji}(n)$ to the synaptic weights, which is proportional, in most of the algorithms, to the partial derivative of a cost function.

Examples of cost functions are given below.

$$\boldsymbol{E(\Theta) = \frac{1}{m}\left[\sum_{1}^{m} \frac{1}{2}(d_k(m) - y_k(m))^2 \right]}$$ *Equation II-6*

Another cost function mostly used for pattern recognition and classification problems is the logistic cost function:

$$\boldsymbol{J(\Theta) = -\frac{1}{M}\left[\sum_{m=1}^{M}\sum_{k=1}^{K} d_{km}\, log(y_k) + (1 - d_{km})\, log(1 - y_k)\right] + \frac{\lambda}{m}\sum_{l=1}^{L-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}} {\Theta_{ij}^{l}}^2}$$

Equation II-7

Where,

□, is the matrix of weights controlling function mapping

k, is the number of neuron in the layer

m, is the number of input-output neuron patterns

d_k, is the desired or target output of the k neuron and

y_k, is the actual output of the k neuron

□, regularization parameter

For evaluating the impact of the adjustment of weights and conclude to a network with sufficient accuracy and avoid performing numerous loops without having a significantly better performance, the system is performing a gradient check. The gradient descent learning rule, commonly used, known as delta rule, is applied during the learning process for the adjustment of weights. The evaluation of the weight correction is given by an equation similar to the definition of gradient and represents a sensitivity factor, determining the direction of search in the weight matrix for each synaptic weight.

$$\boldsymbol{\Delta} = -\boldsymbol{\eta} \frac{\partial \boldsymbol{J}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}, \text{ Equation II-8}$$

Where,

η, is the learning rate parameter, which control the rate of change of the weights and biases

J, is the cost function (in this case logistic cost function)

θ, is the matrix of weights controlling function mapping

However, a key factor involved in the calculation of the weight adjustment is the computation of the error signal $e_j(n)$, of the neuron's output. When the neuron is located at the output node, the calculation of the corresponding error signal is easy, as the network is supplied with a desired, target response. In case of a neuron located at any hidden layer, the problem is more complicated. The hidden neurons are not directly linked to a desired response, so they "share" responsibility for any error made at the final output. The important and complex part, is to know how to penalize or reward hidden neurons based on their response for their share of responsibility. As a result, the error signal should be determined recursively in terms of the error signal of all the neurons to which a hidden neuron is directly connected. This problem is known as the credit-assignment problem, described at (Haykin, 1999).

For the training of MLPs back-propagation algorithms are used. In this study a number of different algorithms were tested in order to conclude at the training procedure that would result in the best possible predictive characteristics. The cost function used for all the cases was mean square error. It is very difficult to know which training algorithm will be the fastest for a given problem. It depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). Back-propagation is a specific technique for implementing gradient descent in weight space for feedforward multilayer networks. The principle of it, is to efficiently compute partial derivatives of an approximating function $F(\boldsymbol{w}, \boldsymbol{x})$, in respect to all elements of the adjustable weights, of the weight matrix $\boldsymbol{w}$, for a given input vector of parameters $\boldsymbol{x}$. Specifically, consider an MLP with an input layer of m_0 nodes, two hidden layers, one output signal and as a result one neuron in the output layer (as the majority of networks used for this study). The weights are ordered in the $\boldsymbol{w}$ weight matrix, by layer, then by neuron in each layer and then by the synapses within a neuron. As defined before $w_{ji}^{l}(n)$ denotes the synaptic weight from a neuron i of the l-1 layer, to a neuron j of the l layer, at the n iteration. The goal is to evaluate the derivatives of the function $F(\boldsymbol{w}, \boldsymbol{x})$, in respect to all elements of the weight matrix $\boldsymbol{w}$ for a given input vector $\boldsymbol{x}$ of m_0 parameters. The multilayer perceptron is also parameterized through its architecture, meaning the number of nodes-processing units located in each layer. To define this, we will insert one more parameter A, which should be interpreted as a symbol linked to the architecture rather than a variable. Now consider A_j^l , denote the part of the architecture extending from the input layer to any node in layer l. As a result, in respect of the activation function φ of the node

$$\boldsymbol{F}(\boldsymbol{w}, \boldsymbol{x}) = \boldsymbol{\varphi}\left(\boldsymbol{A}_j^l\right), \text{ Equation II-9}$$

Following this, the partial derivatives of the approximation function, according to (Haykin, 1999) could be written as

$$\frac{\partial \boldsymbol{F}(\boldsymbol{w},\boldsymbol{x})}{\partial \boldsymbol{w}_{ik}^l} = \boldsymbol{\varphi}'(\boldsymbol{A}_i^l)\boldsymbol{\varphi}(\boldsymbol{A}_k^{l-1}) \text{ Equation II-10}$$

If we assume that we are computing the derivatives of layer $l = 3$, the equation could be rewritten as

$$\frac{\partial \boldsymbol{F}(\boldsymbol{w},\boldsymbol{x})}{\partial \boldsymbol{w}_{ik}^3} = \boldsymbol{\varphi}'(\boldsymbol{A}_i^3)\boldsymbol{\varphi}(\boldsymbol{A}_k^2) \text{ Equation II-11}$$

$$\frac{\partial \boldsymbol{F}(\boldsymbol{w},\boldsymbol{x})}{\partial \boldsymbol{w}_{ik}^2} = \boldsymbol{\varphi}'(\boldsymbol{A}_i^3)\boldsymbol{\varphi}'(\boldsymbol{A}_k^2)\boldsymbol{\varphi}(\boldsymbol{A}_j^1)\boldsymbol{w}_{ik}^3 \text{ Equation II-12}$$

$$\frac{\partial \boldsymbol{F}(\boldsymbol{w},\boldsymbol{x})}{\partial \boldsymbol{w}_{ji}^1} = \boldsymbol{\varphi}'(\boldsymbol{A}_i^3)\boldsymbol{\varphi}'(\boldsymbol{A}_j^1)\boldsymbol{x}_i \sum\nolimits_{\boldsymbol{k}} \boldsymbol{\varphi}'(\boldsymbol{A}_k^1)\boldsymbol{w}_{ik}^3\boldsymbol{w}_{kj}^2 \text{ Equation II-13}$$

Where φ΄ is the partial derivative of nonlinear activation function φ, with respect to its input vector **x** consisting of x_i, input signals. Another aspect of the training process crucial for the performance of the training procedure is the evaluation of the sensitivity of the approximating function $F(\boldsymbol{w}, \boldsymbol{x})$, with respect to any change of any element of the weight matrix-vector $\boldsymbol{w}$. The sensitivity of $F(\boldsymbol{w}, \boldsymbol{x})$, in respect to an element w of the weight vector is defined as

$$\boldsymbol{S}_{\boldsymbol{w}}^{\boldsymbol{F}} = \frac{\partial \boldsymbol{F}/\boldsymbol{F}}{\partial \boldsymbol{w}/\boldsymbol{w}} \text{ Equation II-14}$$

a) Jacobian Matrix in Artificial Neural Network Training

Considering a function $\boldsymbol{f}: R^n \rightarrow R^m$, taking as input a vector $\boldsymbol{x} \in \boldsymbol{R}^n$ and producing as output a vector $\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x}) \in \boldsymbol{R}^m$, the Jacobian matrix is the matrix of all first-order partial derivatives of the vector-valued function. Then the Jacobian, is the matrix of $m \times n$ dimensions, defined as given below

$$J_{ij} = \frac{\partial f_i}{\partial x_j}\text{, or equally described as } J(x_1, \quad \dots, \quad x_n) = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial x_1} & \cdots & \frac{\partial y_n}{\partial x_n} \end{bmatrix}$$

Equation II-15

For any Multi-Layer Perceptron, given a matrix $\boldsymbol{w}$ of the synaptic weights and biases (free parameters), defined and ordered as described, let assume N to be the total number of examples used for the training of the network. Using the previously described methodology, we can compute a set of partial derivatives of the approximating function $F(\boldsymbol{w}, \boldsymbol{x})$ in respect to any element of the matrix $\boldsymbol{w}$, for any input example set $\boldsymbol{x(n)}$ in the training set. Repeating this procedure for all examples in the set will result in a N–by–W matrix consisting of the partial derivatives of any set of example and weight. This output matrix is called the Jacobian $\mathbf{J}$,of the MLP evaluated at the $\boldsymbol{x(n)}$ training set. Each n row is ordered in such way, to represent the Jacobian of a particular n example of the set. The Jacobian matrix provides information regarding how well the network corresponds and indicates its generalization capabilities. A neural network training could be intrinsically ill-conditioned, meaning that the training or the constructed network is poor, leading to a Jacobian matrix that is almost rank deficient. If a number p of columns is almost collinear, then it is expected that the singular values of a p-1, would be relatively small. An ill-conditioned network means that the algorithm obtained only partial information of the possible search directions, causing long and inefficient training. The rank of a matrix equals to the number of linearly independent columns or rows, whichever is the smallest. We can assume that the Jacobian is rank-deficient if its rank is less than the minimum of N or W (S. Saarinen, 1993).

b) Hessian Matrix in Artificial Neural Network Training

Suppose $\boldsymbol{f}$: $R^n \to R$, is a function taking as input a vector $\boldsymbol{x} \in \boldsymbol{R^n}$ and outputting a scalar $\boldsymbol{f}(\boldsymbol{x}) \in \boldsymbol{R}$; if all second partial derivatives of $\boldsymbol{f}$ exist and are continuous over the domain of the function, then the Hessian matrix H of $\boldsymbol{f}$ is a square n×n matrix, defined and arranged as follows

$$H_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j} \text{, or equally described as } H(x_1, \quad \dots, \quad x_n) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$$

Equation II-16

For any Multi-Layer Perceptron, given a matrix $\boldsymbol{w}$ of the synaptic weights and biases (free parameters), the Hessian matrix of the cost function E($\mathbf{w}$), denoted by $\boldsymbol{H}$, is defined as the second derivative of the cost function with respect to the weight vector $\boldsymbol{w}$, as shown below

$$\boldsymbol{H} = \frac{\partial^2 E(\boldsymbol{w})}{\partial \boldsymbol{w}^2}$$ *Equation II-17*

Computation of the Hessian matrix is important in the study and design of Neural Networks, as the eigenvalues of it are linked to the dynamics of the back-propagation learning, as they have a profound influence on the convergence properties of the networks algorithm and the inverse of the matrix provides a basis and insight of simplifying the network via identifying insignificant synaptic weights (Haykin, 1999). Usually the composition of the eigenvalues of the Hessian matrix of the error function, trained by a back-propagation algorithm consists of a small number of large and small eigenvalues and the majority of them are concentrated at the range of medium sized eigenvalues. Wide variation of the second derivatives computed in the

Hessian matrix could be observed over different layers. Commonly, the second derivatives of the first or lower layer are smaller than the last layer's, indicating that the synaptic weight is learning and adjusting slowly at the first hidden layer compared to the fast learning of the last (hidden) layer. Another aspect that influence training and the performance of the outcome network is the correlation between elements of the input vector and the possible correlation between induced neuronal output signals, which results in poor generalization properties and overfitting. In order to reduce learning time, the use of non-zero mean inputs should be avoided. Thus, in most networks, a signal vector $\boldsymbol{x}$ applied in the first hidden layer is processed in such way that for each element of the vector, the mean value is removed, before its application to the following layers. However, in the following layers, depending on the activation function used, the output signal of each neuron could be restricted to a non-zero mean interval. Suppose that a non-symmetrical (over zero) activation function is selected, as the logistic (log-sigmoid), resulting at a restricted output to the interval [0, 1]. This results in a systematic bias on the input of the neurons located at the following layer. A way to overcome this issue, is to use a symmetric activation function, in order to re-arrange the interval over a range in which the mean could be zero. For example, applying a hyperbolic tangent function over the previous logistic function will allow values to range between positive and negative over the interval [-1, 1]. This is important for large networks with a lot of connection and synapses, in order to yield faster convergence.

2. Training Algorithms

a) Levenberg-Marquardt backpropagation

Levenberg-Marquardt backpropagation algorithm is often used as a first training function because usually it is the fastest algorithm in the Matlab toolbox and is highly recommended as a first-choice supervised algorithm. However, it usually, depending on the problem, requires more memory than other algorithms. (MathWorks, MathWorks Documentation, 2018). Levenberg-Marquardt backpropagation algorithm uses the Jacobian matrix and determinant for the calculations, which assumes that the performance (or cost function) is a mean or sum squared errors.

The Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum or mean of squares (as is typical in training feedforward networks), then the Hessian matrix and its gradient can be approximated and computed as:

$$\boldsymbol{H} = \boldsymbol{J}^{\boldsymbol{T}}\boldsymbol{J} \quad \textit{Equation II-18}$$

$$\mathrm{g} = \mathbf{J}^{\mathbf{T}}\mathbf{e} \quad \textit{Equation II-19}$$

Jacobian matrixes contain first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique, which is less complex than computing the Hessian matrix and as a result faster. Techniques that could accelerate the convergence of the algorithm and the principles of Marquardt algorithm are described by M.T.Hagan (Hagan & Menhaj, 1994). The algorithm uses the following update, using the described approximation to Hessian matrix:

$$\boldsymbol{x_{k+1}} = \boldsymbol{x_k} - [\boldsymbol{J^T J} + \boldsymbol{\mu I}]\boldsymbol{J^T e} \quad \textit{Equation II-20}$$

Where, e is a vector of network errors.

When the scalar μ is zero, the eq. *II-19* $\boldsymbol{x_{k+1}} = \boldsymbol{x_k} - [\boldsymbol{J^T J} + \boldsymbol{\mu I}]\boldsymbol{J^T e}$ is just Newton's method, using the approximate Hessian matrix. On the other hand, when μ is large, the same equation becomes gradient descent with a small step size. Newton's method efficiency increases its accuracy while the error reduces, so the aim is to shift towards Newton's method as quickly as possible, when the e vector errors are small enough. Thus, μ is decreased after each successful step (reduction in performance function-better performance) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm. The original description of the Levenberg-Marquardt algorithm is given in (Marquardt, 1963). In Marquardt's original work a maximum neighbourhood method was developed in order to perform an optimum interpolation between the Taylor series method, which faces reduced performance because of the diverge of the successive iterates and the gradient (steepest-descent) methods of which their performance is slowed down due to the slow converge after the first few iterations. The application of this algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundred weights).

b) Resilient Backpropagation

Multilayer networks typically use sigmoid transfer functions in the hidden layers. These functions are often called "squashing" functions, because they compress an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slopes must approach zero as the input gets large. This causes a problem when you use steepest descent to train a multilayer network with sigmoid functions, because the gradient can have a very small magnitude and, therefore, cause small changes in the weights and biases, even though the weights and biases are far from their optimal values. The purpose of the resilient backpropagation training algorithm is to eliminate these harmful effects of the magnitudes of the partial derivatives. To overcome the disadvantages of pure gradient-descent, this method performs a local adaption of the weight changes according to the behaviour of the error function. The adaption process is not affected by the size of the derivatives (Riedmiller & Braun, 1992). Only the sign of the derivative can determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value. The update value for each weight and bias is increased or decreased by a delta factor according to the sign of the derivative of the performance function of two successive iterations. If the sign of the derivative continues to be the same for a number of iterations the magnitude of the weight change increases, in order to improve the performance of the network faster. The approach of computing local learning scheme, which modifies each weight according to the sign of the partial derivative of the weight matrix reduces the number of learning steps in comparison to the original gradient-descent procedure. Another useful feature of this approach, is that the algorithm robust response against the choice of initial, random or predefined parameters.

c) *Gradient - Descent Algorithms*

This group of backpropagation algorithms adjust the weights in respect to the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing most rapidly. In the case of the standard gradient descent algorithms the weights and biases are updated following this method, whereas the learning rate remains constant. An alternative is achieved by adjusting the learning rate of the back-propagation, in order to adapt the local curvature of the error surface. The concept is to increase learning rate when the error decline, as long as the stability of the network is ensured. An aspect that may improve further their learning time is to take into account the momentum of the error function, aiming to avoid local minimum areas and converge faster to the global minimum. A common problem this group of algorithms face is that they depend on the starting point. Meaning that, by one direction minimization process followed by these algorithms, not imply necessary that the function is minimized on the weight space. A graphic representation of the described procedure and problem is presented.

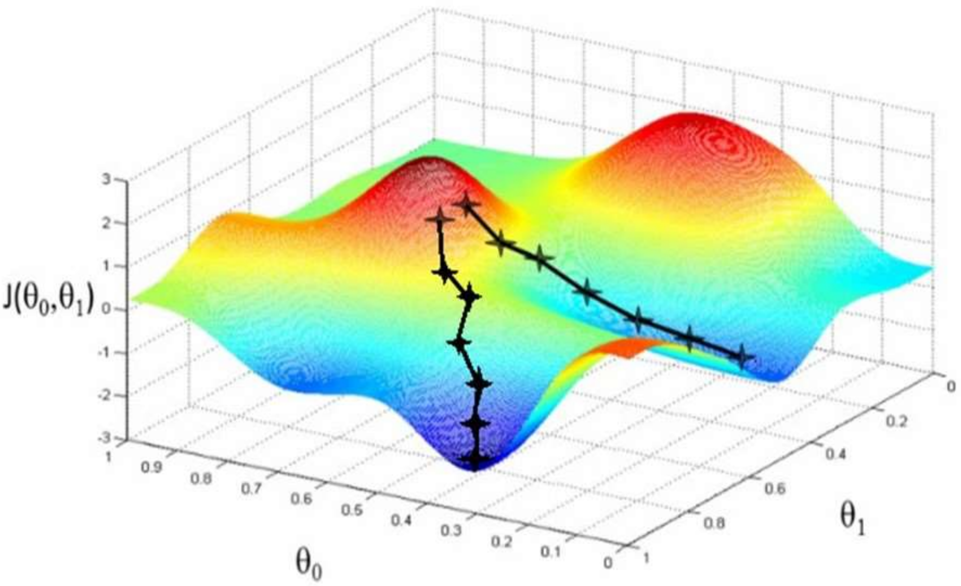


Figure II-6 Gradient Descent Algorithm

Where $\mathbf{J}$, in this case is the logistic cost function and θ_n, are the weight matrixes of n iteration.

The weights are updated following the equation: $\theta_n = \theta_{n-1} - a\frac{\partial J}{\partial \theta}$ *Equation II-21*

Where a is the learning rate of the given iteration.

It turns out that, although the function decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms, a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. Such approach is described by (Moller, 1993) , where a conjugate gradient method (scaled conjugated gradient – scg), which avoids the repeating line search per iteration in order to scale each step size is presented. In most of the training algorithms a learning rate is predefined to determine and limit the magnitude of every step of the weight update. In most of the conjugate gradient algorithms, the step size is adjusted at each iteration. A search is made along the conjugate gradient direction to determine the step size, which minimizes the performance function along that line. Some search functions are best suited to certain training functions, although the optimum choice can vary according to the specific application. An appropriate default search function is assigned to each training function, but this can be modified by the developer. Conjugate direction methods follow the same general optimization strategy but choose the search direction and the step size more carefully by using information from the second order approximation.

d) BFGS Quasi-Newton Backpropagation

BFGS Quasi-Newton Backpropagation is an alternative to the conjugate gradient methods based on Newton's method for faster optimization. The equation representing the method's computation step is

$$\boldsymbol{x_{k+1}} = \boldsymbol{x_k} - \left[\boldsymbol{A_k^{-1}}\right]\boldsymbol{g_k} \quad \textit{Equation II-22}$$

Where, $\boldsymbol{A_k^{-1}}$ is the Hessian matrix of second order derivatives of the performance index at the given values of the weights and biases of any iteration. Newton's method converges faster than the conjugate gradient method when the error becomes relatively small. However, computing Hessian matrix for feedforward neural networks is a complex and computationally expensive process which results in slowing down the training. To overcome this problem and "avoid" repeating the computation of the Hessian matrix, there is a class of algorithms that is based on Newton's method, but which does not require calculation of second derivatives in each iteration. These are called quasi-Newton (or secant) methods. Their approach is to update an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient. The quasi-Newton method that has been most successful in published studies is the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update. One of the first attempt to generate a sequence of approximations to the inverse of the Hessian matrix was given by (Shanno, 1970). An improved approach on BFGS is described by (Nawi, R.Ransing, & S.Ransing, 2016) where the approach claims that improves the training efficiency of standard backpropagation algorithm by adaptively modifying the initial search direction, with a resulted effect on 15% reduction on the required iterations to converge. Another approach to a modified BFGS algorithm was given in (Yuan, 1990). In this approach the author claims to satisfy the quasi-Newton condition via an interpolation condition in which the gradient value of the local quadratic model matches the objective function of the previous iterate. This modified approach on BFGS algorithm preserves the global and local super-linear converge properties of the algorithm. Compared to the conjugate gradient method, this category of algorithms requires more computation power in each iteration and more storage, however it generally converges in fewer iterations. The computed Hessian approximation must be stored and as a result due to its dimensions (**n**×**n,** where **n** is equal to the number of weights and biases) this makes BFGS inefficient for very large networks.

e) One Step Secant Method

To address the inherent problem of BFGS algorithm requiring more storage and computation in each iteration than the conjugate gradient algorithms, there is need for a secant approximation with smaller storage and computation requirements. The one step secant (OSS) method is an attempt to bridge the gap between the conjugate gradient algorithms and the quasi-Newton (secant) algorithms. This algorithm does not store the complete Hessian matrix; it assumes that at each iteration, the previous Hessian was the identity matrix. This has the additional advantage that the new search direction can be calculated without computing a matrix inverse. This algorithm requires less storage and computation per epoch than the BFGS algorithm. It requires slightly more storage and computation per epoch than the conjugate gradient algorithms. It can be considered a compromise between full quasi-Newton algorithms and conjugate gradient algorithms. This method as described by (Battiti, 1992), responds sufficient for the on line first order backpropagation even in large-scale classification problems, however for high precision mapping its result may be questionable.

f) Bayesian regularization backpropagation

Bayesian regularization backpropagation algorithm is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization. The limitation of it lies in the method this algorithm uses. In order to calculate the Jacobian matrix, the performance function should be either mean or sum of squared errors. Therefore, networks trained with this function must use either the mean square error or the sum of square error performance function. Also due to the same limitation, Bayesian regularization backpropagation algorithm can train any network as long as its weight, net input, and transfer functions have derivative functions. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities. This algorithm takes place within the Levenberg-Marquardt algorithm, while the computation of the derivatives and the Jacobian matrix is done according to the equation and methodology described at II.C.2.a).. The adaptive value μ, is increasing until the change monitored, results in a reduced performance index. Then, the change is applied to the network and the factor μ is decreased. This process penalizes over flexible and over complex models, which over fit training data, and helps detect poor underlying assumptions in learning models. (MacKay, A practical Bayesian Framework for Backpropagation Networks, 1992) The concept is that this procedure reassures that the learning model matches to the given problem.

3. Division of data set

The data available for the training and design of the network is usually divided initially, into three mutually exclusive sets. Further training of the network can be done, in the basis of a new set of data compliant and valid for the given problem. Attention should be given to the generalization properties of the network, while over training, complex and over sensitive weight updates could result in poor fit of the network to the problem. The three sets in which available data is usually divided are:

- Training set. This set is used in order to update and optimize the synaptic weights and biases of the network, in the basis of minimizing the applied cost function.
- Validation set. This set is used for the tuning and evaluation of free parameters as it is used for comparison between networks with different characteristics, in terms of weights and free parameters.
- Test set. This set is used in order to map network's predictive ability and generalization properties. This data set is applied after the training of the network and do not affect any of the properties of the network.

The common practice, known as holdout validation, is to select training, validation and test set as a percentage of the data available. There is also another way of selecting a validation set, usually used for small datasets; the k-fold validation. This scheme divides the available data in k disjoint folds. Subsequently, trains the algorithm k times using each time a different fold as the validation set and the remaining as training set. After each passing the corresponding validation error is calculated. The validation error of the network is equal to the average of all calculated validation errors. The number of the folds k is user defined (Margari, 2017).

III. Data acquisition and processing

A. Vessel Particulars-General information

The vessel used for the purpose of this study is a 319,000 TDW VLCC of a modern design, delivered to Maran Tankers Management Inc. in 2016. Following company's policy, the subject vessel is equipped with innovative systems promoting better performance and energy efficiency. Equipment and design innovations relevant to this study are the installation of a Mewis duct and a bulbous rudder, which increase vessel's propulsion efficiency. The hull is optimized for the estimated operational profile. A vertical stamp bow design (no bulbous bow) was selected as it is proven to be more efficient for the range of speeds the vessel is expected to sail and results in better performance over the wave spectrum it is expected to face based on the trading route the vessel was designed for, according to a study made by the yard. Below a table of vessel's particulars is presented.

Length O.A.	336.00 m
Length B.P.	330.00 m
Breadth (molded)	60.00 m
Depth (molded)	30.50 m
Draft Design (molded)	20.80 m
Draft Scantling (molded)	22.50 m

Table 3: Particulars

The propulsion plant is a de-rated ultra-long stroke diesel engine.

B. Data Selection

In the Performance Monitoring and Analysis Systems chapter we analysed the components affecting vessel's performance, as well as the parameters linked to each physical problem. It has become clear that accurate data, obtained automatically with a high rate of data acquisition is one of the most important requirements for in deep performance monitoring. The quality of the collected data depends on the data conditioning characteristics, sensor characteristics and maintenance, environment of the sensor, and the behaviour of the vessel. One aspect equally important to the rate of data acquisition is data quality. In our case, data quality is of great importance, as we do not use any predefined equations or analytical connection to evaluate vessel performance, but we rely on the training of a network. In this approach, as described at the previous chapter (Feed-forward Multi-Layer Perceptron), the importance of the data collected and their properties, as well as the physical and statistical connection between the variables is crucial. The correct selection of input parameters, that fulfil in the best possible way the above required properties, could make a huge difference in the predicting abilities of the network. Dimensionality reduction is an important step in data analysis, because it can help improve model accuracy and network's performance, improve interpretability, and prevent overfitting. As a result, choosing only the parameters, which include all the information needed to define the problem and avoid inserting signal with low or none information could result in a much better outcome. As a result, balancing correlation between input-signals and connection of each of them to the physical problem, keeping in mind how to keep network's properties balanced are things that need to be under consideration.

Keeping all this in mind, we proceed to the selection of parameters based on the physical problems we want to address. As discussed above, the selection of parameters is a crucial part of the modelling, as it heavily affects the neural network's properties. In the following, the different resistance components are presented. The analysis of the different parameters contributing to each resistance component, lead us to the selection of the input vector, which we believe describes sufficiently our problem.

1. Calm water Resistance

Calm water resistance of the clean hull and propeller (no fouling or deformation), as described in I.D.1, consists of two main components, frictional and pressure resistance. However, propelling the vessel with its propulsion plant, alters the calm water resistance, as the pressure field changes due to the running propeller and the interaction of the propeller with the ship's hull.

Typically, the total resistance of the hull, based on the resistance towing test, is described by a coefficient:

$$\boldsymbol{C_T} = \frac{\boldsymbol{R}}{\frac{1}{2}\boldsymbol{\rho S V^2}} \quad \text{, Equation III-1}$$

Where,

R is the measured resistance force

ρ is the fluids density

S is the wetted surface

And V is the speed

The effect of the interaction of propeller and hull is demonstrated by the self-propulsion test. For this analysis, we used the results of such tests, in addition to the sea trial, in order to produce a baseline power curve in calm water for the vessel in question. These data are commonly available for design draft and ballast condition, as well as in some cases, scantling draft. For different draft an approximation is suggested (ISO, Ships and marine technology-Measurement of changes in hull and propeller performance, 2016), based on a corresponding speed, approximated by the ratio between the different displacements. Reference data from the closest available displacement curve shall be used as baseline and the remaining variation is suggested to be corrected by the Admiralty formula, shown below:

$$V_2 = V_1 \left(\frac{\Delta_1^{2/3}}{\Delta_2^{2/3}}\right)^{1/3} \quad \text{Equation III-2}$$

This approximation is not accurate, but is oriented to focus in small draft difference between the actual and the reference draft. For conditions where, the hydrodynamic characteristics change, the submerged geometry is different, or the relation of speed and displacement for the specific ship type is not valid, this approximation is inaccurate.

The approach used for this evaluation is based on an approximation methodology, aiming to balance the weight matrix of the neural network. The vessel in question is a VLCC, with relatively high frictional resistance compared to other resistance components. Frictional resistance is proportionate to the wetted surface and related to the speed. The big advantage of the neural network approach, is that it is not necessary to know any physical relation between parameters, as long as all the necessary parameters are inserted in the network. Based on this property of the neural network, we assume that the problem is well dimensioned by inserting the following parameters.

- Speed
- Wetted surface
- Water density

For the above in order to reduce the input dimensions we proceed as following.

- Speed is inserted as a parameter
- Wetted surface is assumed well dimensioned as a function of draft, trim and list, as the network is trained by operational data of the subject vessel.
- Water density is not taken into account, because the variation of it is low and during the preliminary testing, using it as an input parameter increased noise and did not increase prediction accuracy of the network.

2. Added wave resistance

This component is related with the action of waves on the hull as well as with the induced ship motions. As described, it can be attributed to several physical phenomena. Added wave resistance commonly is decomposed to resistance due to motions induced by the waves and the energy loses due to reflection of short length waves.

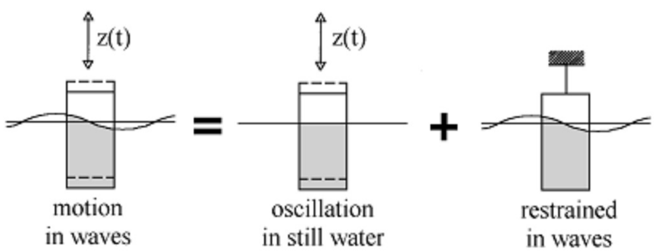


Figure III-1 Added wave resistance decomposition

However, the interaction of those two components is creating a complex problem, difficult to describe and analyse. For short incident waves, the principle component of added wave resistance is the reflection of waves.

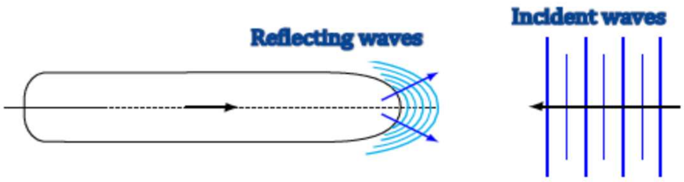


Figure III-2 reflection/diffraction of waves

For waves of medium length, similar to the length of the vessel, the main part of added wave resistance is related to radiation. Radiation is produced by the induced motions of the vessel (primarily heaving and pitching, and secondarily rolling) due to the seaway.

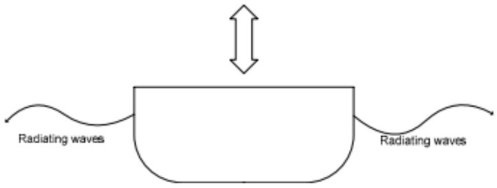


Figure III-3 Radiation

For very long waves, it is assumed that the vessel follows the wave pattern with less impact to the added wave resistance. In our case, we can safely assume that in most of its lifetime the principle component of added wave resistance is related to the reflection and diffraction of waves, as the length of the vessel is 330m (between perpendiculars) and it is not likely to face waves of this length. However, our approach is not restricted to model only one of this physical phenomena. Liu S. conducted research on the modelling of the added wave resistance in respect to vessel's particulars and condition (S. Liu, 2015). Commonly, the added wave resistance is estimated through wave characteristics and a number of parameters related to the vessel's response, hydrodynamic and seakeeping characteristics. As a result, we can conclude that for a given loading condition, wave added resistance may be expressed as follows:

$$\boldsymbol{R_{aw} = f(V_s, H_{sw}, a_w, T_{sw}, H_{ss}, a_s, T_s)}$$ *Equation III-3*

Where,

$\mathbf{V_s}$, is the speed of the vessel

$\mathbf{H_{sw}}$, is the significant wave height of the wind generated waves

$\mathbf{a_w}$, is the angle of incidence of wind generated waves

$\mathbf{T_{sw}}$, the peak period of the wind generated waves spectrum

$\mathbf{H_{ss}}$, is the significant wave height of swell waves, long low frequency waves

$\mathbf{a_s}$ **,** is the angle of incidence of swell waves

$\mathbf{T_s}$, is the period of long low frequency swell waves

3. Wind Resistance

As described, wind resistance depends upon the vessel's apparent speed and upon the area and the shape of the upper body, exposed to wind forces. The resistance force can be estimated by the equation (ISO, Ships and marine technology-Measurement of changes in hull and propeller performance, 2016):

$$\boldsymbol{R_{rw} = \frac{1}{2}\rho_{\alpha} v_{rw}^{2} A c_{x}(\psi_{wr})} \quad \text{Equation III-4}$$

Where,

ρ_{α} , is air density

v_{rw} , is the relative wind speed at the reference height

A, is the transverse projected area in current loading condition

C_x , is the wind resistance coefficient, dependent on the wind direction of the relative wind

ψ_{wr} , is the relative wind direction at the reference height

The wind force coefficient C_X can be found by wind tunnel tests on a particular ship model or by various approximation models. The two semi empirical models commonly used, when wind tunnel tests are not available, which comply with the ISO 19030 and ISO 15016 requirements are Isherwood and Fujiwara. The measured wind will have to be corrected for the height of the anemometer placement on board the ship. The wind is varying in strength with height and the wind resistance models used are to a certain reference height. The wind velocity variance with height can be corrected by (15016, 2015)

$$\boldsymbol{V_w(z_{ref}) = V_W(z) \cdot \left(\frac{z_{ref}}{z}\right)^{\frac{1}{7}}} \quad \text{Equation III-5}$$

Where,

$\mathbf{V_W}$, is the measured wind velocity

$\mathbf{z}$, is the height of the anemometer

$\mathbf{z_{ref}}$, is the reference height used in the wind resistance model as described in the subject ISO 15016

For this study, wind resistance coefficient computed by wind tunnel tests are available. However, due to the small impact of wind resistance as part of the total resistance of the subject vessel, inserting all these parameters as an input to the neural network resulted in poor network's performance and increased noise, as the weights of these parameters are relatively small and the weight matrix becomes unbalanced. To avoid this effect, only relative wind speed, measured at the anemometer, and the relative direction of wind is used. This includes the assumption that wind resistance component is well dimensioned through these two parameters in addition to the loading condition and operational parameters already inserted and the fact that the network is trained with service data.

4. Shallow water effect

As described, shallow water effect consists of two basic components, the added resistance due to the increased sinkage and dynamic trim when sailing in shallow water and the added resistance due to the change of wave patterns. An approximation of speed loss due to these effects, is given in the work of (Lackenby, 1963):

$$\frac{\Delta V_s}{V_s} = \mathbf{0.1242}\left(\frac{A_M}{h^2} - \mathbf{0.05}\right) + \mathbf{1} - \left(\boldsymbol{tanh}\frac{gh}{V_s^2}\right)^{\mathbf{1/2}} \textit{for } \frac{A_M}{h^2} \geq \mathbf{0.05} \quad \textit{Equation III-6}$$

Where,

$\mathbf{\Delta V_s}$, is the speed loss due to shallow water

$\mathbf{V_s}$, is the vessel's speed

$\mathbf{A_M}$, is the midship section area under the current water line

$\mathbf{h}$, is the water depth

In the framework of this thesis, due to the trading pattern of the vessel is was decided to filter out the period when the vessel was sailing in shallow water as it is a very short period of time compared to the overall sailing time. The filtering was done based on the condition of the above equation, but for $\mathbf{A_M}$, of the design draft.

5. Trim effect

Trim is known to alter the calm water resistance of the vessel by altering the flow and the pressure field. It also has an impact at the inflow of the propeller. However, due to design limitations of the subject vessel at each condition the range of available trims is relatively small. Trim is inserted as an input parameter, along with other parameters, which are related to its effect, like speed and draft. The neural network is relating these parameters with all the corresponding synapses weights included and correlate these input parameters of the input vector to the final predicted power.

6. Steering effect

Steering effect indicates the resistance contribution of the drag force due to rudder angle, and the lift produced by the rudder when leading to a yaw angle, since the ship will counteract the lift from the rudder. An approach to the rudder induced resistance is given by (Kijima, 1990). Due to the complexity of this approximating calculation and the fact that is oriented for standard rudder geometries, it is selected to use the rudder indicator reading and all the other parameters related, which are already included at the input vector of the neural network, and let the network approximate their effect and synapses. The computation of the impact of steering could have been done separately, however the rudder of the subject vessel is not of conventional design, as except of its different geometry it has a rudder bulb attached, which is design to improve the outflow of the propeller.

C. Data logging sensors on-board and other data acquisition sources

Following is the list with the data acquired at the initial stage:

1. Speed through water (log) Doppler – Echo Sounder
2. Rudder indicator
3. RPM, torque meter readings and computed shaft power
4. Wind anemometer (relative wind speed and direction)
5. Position signal from GPS
6. Vessel's heading through the Gyrocompass
7. Draft (dynamic) at aft forward & amid ship starboard and port / computing trim and list
8. Air and sea water temperature
9. Weather provider
   i. Significant wave weight
   ii. Wind-wave direction
   iii. Swell significant wave weight
   iv. Swell direction
   v. Swell period

Sensors type and accuracy are described below. Examples of their use are analysed.

1. Speed through water (log) – Echo Sounder

a) Speed through water (log)

The speed through water (log) is a crucial source for data in the performance calculation. The accuracy of the sensor depends on the calibration and on the manufacturer specifications. An offset between speed log readings and the actual speed, over a significant period of time, will indicate the need for calibration. Accuracy of speed log used, when calibrated and well maintained, is stated by the manufacturer to be ±1% or 0.1 knot, whichever is greater. However, a series of factors could influence the measurements. Measurement of the speed through water depends on acoustic reflection from solid particles in the water. In extremely clear water the variation on the quantity of scatters may affect signal return. A common problem, attributed to poor design, in most cases, is the presence of aeration at the area, where the transducer is placed. Aerated water under the transducer may reflect sound energy which could erroneously be interpreted as sea bottom returns. Sailing in heavy weather may be an additional source of this effect as it creates non-laminar flow around the transducer. By placing the transducer near the bow the effect of non-laminar flow is reduced considerably.

b) Echo Sounder

Two sensors are installed on the ship – one at the forward section and one at the aft, approximately below the accommodation. The frequency ranges for the sensor are in the interval from 50 to 320 kHz and the measuring accuracy is in the order of 2.5% of the measured depth, accomplished by 3 beams. The echo sounder is used in confined waters for navigational purposes, for which the echo sounder frequency is set to 50 kHz. At this frequency the sea bed detection level is around 90-150 m depending on sea water salinity and temperature.

2. Rudder Indicator

The electric rudder angle indicator equipment is used for measuring and monitoring the actual rudder angle. The rudder indicator measures the rudder angle continuously and the measuring accuracy is usually below the range of +/- 0.5° at common angles and +/- 1.5° at hard over rudder. The rudder angle indicating system is composed of one transmitter and one or more receivers. The transmitter is installed in the steering gear room and connected to the rudder through a lever and a coupling rod. The transmitter is designed to rotate by four times the actual angle of the rudder turned though a gear mechanism. This makes the pointer scale on the dial turn by four times as much as the actual rudder angle, for easy and correct readout.

3. RPM, torque meter readings and computed shaft power

Shaft power meter is an instrument for continuous measurement of torque, revolutions, and as a result power on a rotating shaft. The technology used for this purpose is strain gauges, arranged on a ring, placed on the shaft. The instrument consists of an aluminium ring part clamped on the shaft, before the intermediate bearing, a stationary unit located next to the shaft and a terminal junction box for the transmission of the signal and power connection. Shaft ring contains additional electronic components for signal processing, while serving as a protection for the strain gauges. According to manufacturer, the induced instrument's accuracy is +/- 0.5% over torque and power, while the accuracy of the shaft's revolutions is measured at +/- 0.1%. The basic principle with which this arrangement works is that any deformations of the strain gauges are transferred into voltages deviation, which determine the strain on the shaft. The typical torque measurements on a propeller shaft are in the order of 330 micro strains and the strain gauges are able to detect changes in the order of 1.5 micro strains.

4. Wind anemometer (relative wind speed and direction)

The anemometer provides wind direction and speed signals simultaneously from a signal transmitter. The wind anemometer is a helicoid propeller type with a vane for direction measurement. The wind direction is detected as a rotating angle of the vertical tail-fin (vane) and a body with respect to the stationary part, transmitter to the synchro motor type transmitter, and read from the rotating angle of the synchro motor receiver. The wind speed is measured by the helicoid propeller, while it is translated to a voltage by the generator added converter which is directly coupled to the propeller and the voltage is rectified and directly read on a voltmeter, calibrated in instantaneous wind speed. The anemometer should be placed as high as possible and located on an area, on which to avoid interaction with the sea surface or any structure that could result in altering the air flow. The measuring accuracy provided by the manufacturers is in the order of +/- 0.3 m/s or 1% of the wind speed and +/- 3° of the wind direction, in common arrangements.

5. GPS

The GPS gives information about the speed of the vessel. The speed, via GPS, is measured above ground whereas the speed measured by the ship's log is speed through water. In cases where the ship is not subject to any set and drift caused by current, the two measured speeds should be similar. Thus, GPS speed is also very useful, in order to identify log speed, or speed through water malfunction.

6. Gyrocompass

The gyrocompass determines the vessel's heading using gyro sphere in respect to true north. The heading could be used in combination to the wind anemometer to calculate true wind speed and directions based on relative measurements on-board. The compass is connected to the autopilot which steers the ship when sailing. The autopilot keeps the ship's course as set by the navigator correcting for any environmental disturbances from waves, wind and currents, as well as the ship's sailing conditions. Rudder commands from the autopilot usually are given partly based on settings applied by the navigator and partly by a mathematical model of the ship programmed in the autopilot. To achieve the most economical steering for the vessel it is essential that settings given to the autopilot are in accordance with weather and load conditions.

7. Draft readings

Draft information can be given as manual input at the start of each leg or via sensors on-board. In our case, sensors using pressure readings at various areas of the vessel's bottom are used to compute drafts at different longitudinal and transverse positions. During sailing the draft information is updated continuously, with the same frequency as the other automatically logged parameters and is validated at port through calculating the loading at still water.

D. Data preparation

Practically all signals from sensors on-board ships contain outliers and must be filtered before they are further processed. Outliers occur due to electrical noise, errors in data transmission, incorrect readings from sensors, poor calibration, or due to other issues. Data preparation involves retrieving, compiling, filtering and validating of collected data, in order to provide a structure, format and quality suitable for further processing. Identifying malfunction on any step of this process enables us to act correctively and rectify the error source if the data are found invalid. A common problem often faced is drifting of sensors (e.g. torque meter), which cannot be identified by an error in data collection, however it results in an incorrect description of the vessel's condition. They can be identified using statistical techniques such as the Chauvenet's criterion, suggested in (ISO, Ships and marine technology-Measurement of changes in hull and propeller performance, 2016), Peirce's Criterion or median filter or by means of cross validation with other parameters. The Chauvenet's and Peirce's criterion (Ross 2003), which both base the rejection of outliers on a statistical probability, are found not satisfactory in transient conditions. An advanced method to improve system monitoring reliability and multi sensors fusion, applicable to marine performance systems is described by (Lajic, Fault - Tolerant Onboard Monitoring and Decision Support Systems, 2010). During periods of transit, ship performance should not be logged for performance monitoring. In order to identify these periods, a number of parameters must be continuously monitored and these periods should be identified by calculating the rate of change in some basic parameters. During this study filtering and validation problem is not addressed. Data retrieval, compiling, validation, and outliers filtering is done prior receiving the data for this study. A basic filtering is applied only at the data used for training, based on rate of change of shaft's RPM. The format of the data received is demonstrated in a graphic form in the Figure III-4, plotted on an hourly interval.

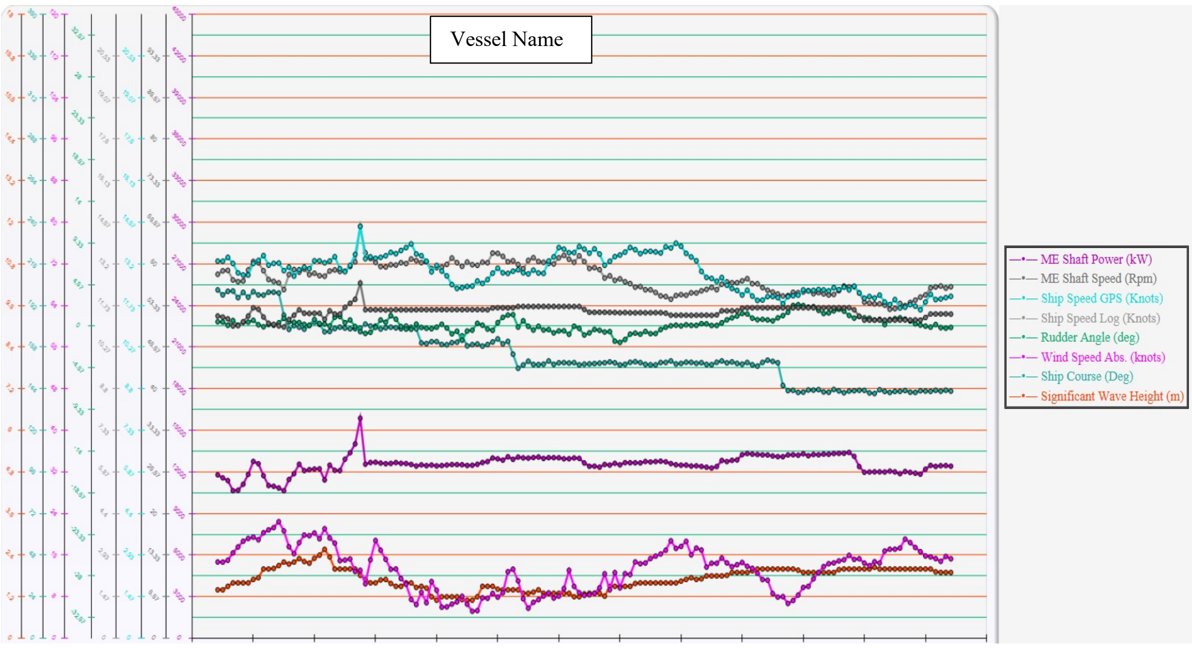


Figure III-4:Live data

E. Parameters selected for Neural Network input vector

As discussed in previous chapter (II. Neural Networks) inputting parameters which contain the same information, or correlate with other parameters, result in reducing neural network's ability to generalize and lead to overfitting. In order to limit this effect, a preliminary evaluation was done. The evaluation of the input signals was done by creating and plotting a matrix of scatter plots of the data input, grouped by the loading condition of the vessel (ballast, design laden, scantling) in order to identify correlated parameters. Each individual set of axes in the presented figure contains a scatter plot of a column of data against another column of data. The plotting is divided in different sets of input parameters, based on their category, and clustered according to the loading condition. Red points are categorized as ballast condition, blue as the design draft and black cluster consists of the data at scantling draft.

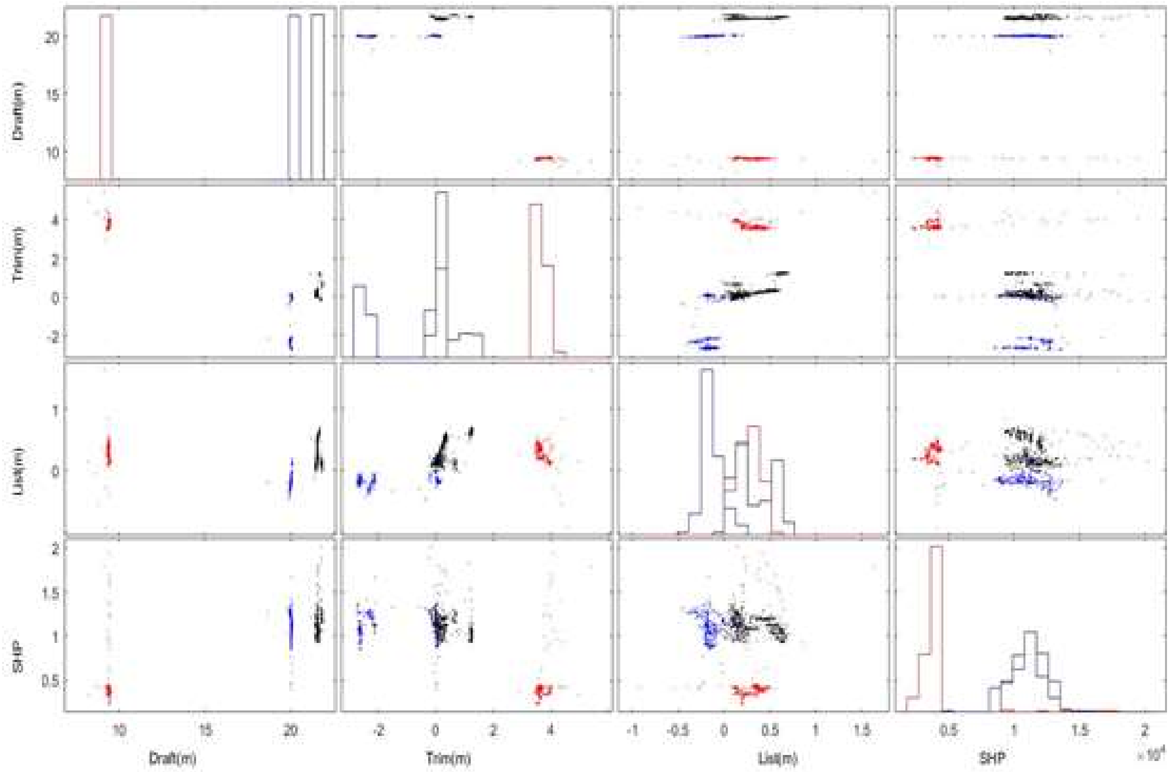


Figure III-5 : Loading condition parameters

From the above graph, is can be observed that trim is heavily correlated with draft, as the design constrain of a fully submerged propeller at ballast condition is only fulfilled for trims above 3m. Also, for the subject vessel an optimization test from the yard and another third party, concluded that trim at the range of 3.5 meters at the normal ballast speeds is the optimum and as a result the vessel is usually operating at this trim range. For laden and especially close to scantling condition, trim is more difficult to change due to the greater momentum to change trim and the draft limitation. Similar optimum trim analysis concluded that from the possible achievable trims, trim by the bow of 0.5 meters results in the minimum calm water resistance at the design draft. For the purpose of this study, keeping all three of the above parameters (draft, trim and list) is selected. In order to avoid the heavy effect of the draft to the predicted shaft power (SHP), demonstrated at the above graph, calm water resistance and sea trials, were used to establish a base load which was subtracted from the measured shaft power. With this approach the impact of the draft to the predicted "added" power is reduced.

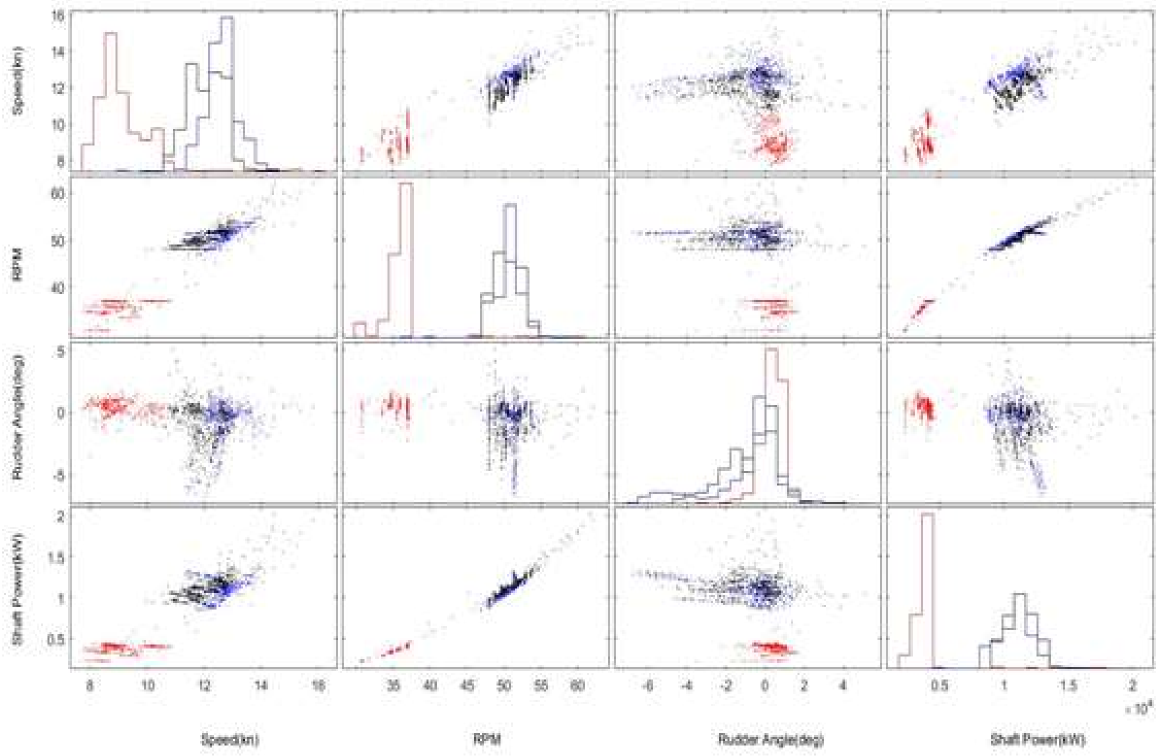


Figure III-6 Operational parameters

As expected we can observe the strong relation of the delivered shaft power with the rpm of the vessel, concluding that including rpm as an input parameter will result in unbalancing the network and dominating the prediction. As a result, it was decided to exclude rpm from the list of input parameters. It is useful to note that all the data used for the initial training are extracted for known conditions, where the vessel's hull and propeller are good. **The period used is selected to be the first two months after delivery of the vessel and a few voyages (approximately two months of sailing) after the first underwater hull inspection and propeller polishing (7 months after delivery).** The inspection's findings were that no fouling was observed on the hull and the propeller was polished back to the Rupert scale A. A minimal change at rpm and power relation, which is expected as the hull and propeller are getting fouled, would reduce dramatically the ability of the network to evaluate vessel's condition. This effect led us to exclude rpm from the input parameters vector, however it was used to identify periods of change, which should necessarily be excluded from the training set as they do not represent a normal operational condition that the network should be trained with. It is extremely crucial to narrow training data to steady and normal operational condition, where the hull and propeller are clean, in order to train sufficiently and avoid creating with poor generalization capabilities.

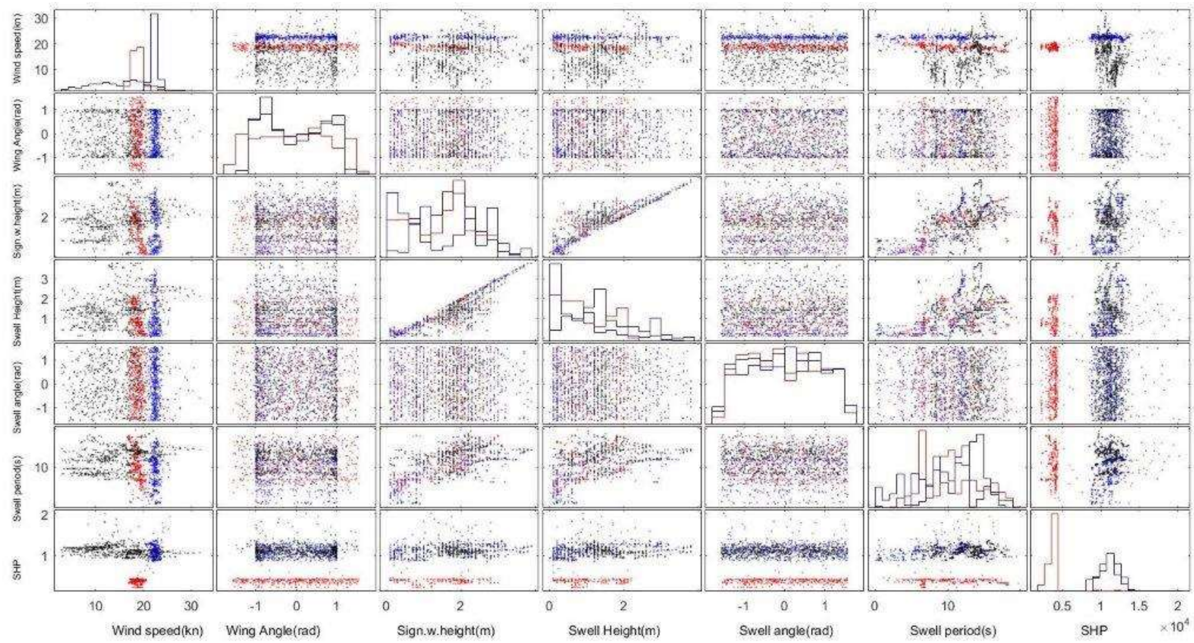


Figure III-7 : Weather condition parameters

Unfortunately, it so happened that the weather condition and especially relative wind speed, on ballast and design draft was limited to a short range, in contrast with the observations at the scantling draft. This could mean that the generalization capabilities of the network at these drafts may not be very good at significantly different weather condition as the synaptic weights are not trained in similar conditions. An additional training set, maybe required, however this could be evaluated at a later stage.

After assessing the correlation between the parameters, we conclude at the below list of parameters used for the model.

1. Speed through water (log) Doppler – Echo Sounder
2. Rudder indicator
3. Wind anemometer relative wind speed
4. Wind anemometer relative direction
5. Average draft (starboard and port) at amid ship
6. Trim
7. List
8. Significant wave weight
9. Swell significant wave weight
10. Swell direction
11. Swell period

IV. Implementation of the Artificial Neural Networks

The development of the Artificial Neural Networks for the approximation of the required shaft power for any given loading and weather condition assuming clean hull and propeller was carried out using MatLab. MatLab is a multi-paradigm numerical computing environment and proprietary programming language developed by MathWorks, widely used in numerical analysis, allowing matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, C#, Java, Fortran and Python.

Cleve Moler started developing MATLAB in the late 1970s (Moler, 2018). He designed it to give his students access to LINPACK and EISPACK without having to learn Fortran. It soon spread to other universities and found a strong audience within the applied mathematics community. Jack Little, an engineer, was learned about the development of MATLAB at its primary form, during a visit Moler made to Stanford University in 1983. Recognizing its commercial potential, he joined with Moler and Steve Bangert. They rewrote MATLAB in C and founded MathWorks in 1984 to continue its development.

Except from a library of functions and a compiler, MATLAB includes numerous toolboxes specially designed for specific applications and analyses. One of these toolboxes is focusing on machine learning and Artificial Neural Networks. This function library assists the user to design, adjust and develop Multi-Layer Perceptron networks, providing a powerful tool for managing and handling networks.

Starting with the initial selection of input parameters-vector as described previously, developing the network consists of the determination of a number of network's particulars and parameters. Concluding to the MLP that fits best the problem is a vague process. Different division of the dataset to the subsets (training set, test set, validation set) as well as the initial weights given to the weight synapses are affecting the resulting network and its performance. Each configuration examined in the current study is determined by the following network and design parameters:

- The training algorithm used
- The transfer functions used in each layer of every developed network
- The number of hidden layers
- The number and type of neurons allocated in each layer
- Learning rate at the training process or in some cases of algorithms even the training rate of each iteration.

Starting the evaluation of networks and narrowing the number of the above parameters, in order to conclude slowly to the MLP that suits better the problem, an evaluation of the training algorithms was initially done. This approach was selected due to the observation that the selection of the training algorithm affects significantly the network's prediction capabilities and generalization properties. This trial approach started by testing the training algorithms on a number of architectures, six per algorithm defined by the number of neurons in each of the two layers. The decision to use two hidden layers was made during the preliminary stage as the architecture with one hidden layer was evaluated as simple and architectures with three or more hidden layer were too complicated and seem to generalize poorly compared to the networks with two hidden layers. The training rate for the algorithms, which are determined by their learning rate, was left constant at the suggested value, for the initial evaluation. Typically, the transfer functions used were, for the input layer to the first hidden layer the hyperbolic tangent sigmoid transfer function, followed by a linear transfer function connecting first hidden layer to the second. Lastly, as commonly used at MLPs the transfer function used for the connection of the second (and last) hidden layer to the output layer was again selected to be a linear transfer function. This set of transfer functions was selected according to a quick evaluation on the Levenberg-Marquardt algorithm, which is the fastest algorithm of the below tested. However, tests with different sets of transfer functions were made for different algorithms, in order to evaluate if this assumption is affecting significantly the performance of the neural networks trained. A way of comparing networks with different parameter values is to assess their performance by measuring the error on an unknown data set by similar cross-validation techniques. The evaluation was made based on the mean square error performance (cost) function of the validation set. The algorithms tested, are listed below:

- Levenberg-Marquardt backpropagation
- Resilient Backpropagation
- Gradient - Descent Algorithms
    - Scaled Conjugate Gradient
    - Conjugate Gradient with Powell/Beale Restarts
    - Fletcher-Powell Conjugate Gradient
    - Polak-Ribiére Conjugate Gradient
    - Variable Learning Rate Backpropagation
- BFGS Quasi-Newton Backpropagation
- One Step Secant Method
- Bayesian regularization backpropagation

A detailed description of the tested algorithms is given at II.C.2 “Training Algorithms” chapter.

The initial evaluation of the training algorithms is presented at the following table. The values presented demonstrate the properties of the best performing network based on each algorithm, over a regularized output and target set. The following results, led us to select Bayesian regularization backpropagation algorithm as the primary algorithm. In the course of this study, alternative algorithms with acceptable initial results have been tested, however, Bayesian regularization backpropagation performed better at all stages. This result is in accordance with the study of (Foresee & Hagan, 1997). The issue studied at this paper, was the use of Bayesian regularization to prevent overfitting in neural network training as developed by David MacKay. The significant drawback of this method is that it requires the computation of the Hessian matrix of the performance index. This results in an extended training time period and increases the required computational power compared with other algorithms. A brief overview of the training time needed depending on the selected algorithm is given at (MathWorks, 2018).The Bayesian regularization algorithm generally works best when the network inputs and targets are scaled so that they fall approximately in the range [−1,1]. To fulfil this requirement, which improves further the performance of a network, all parameters (input and output), were scaled to fit this range.

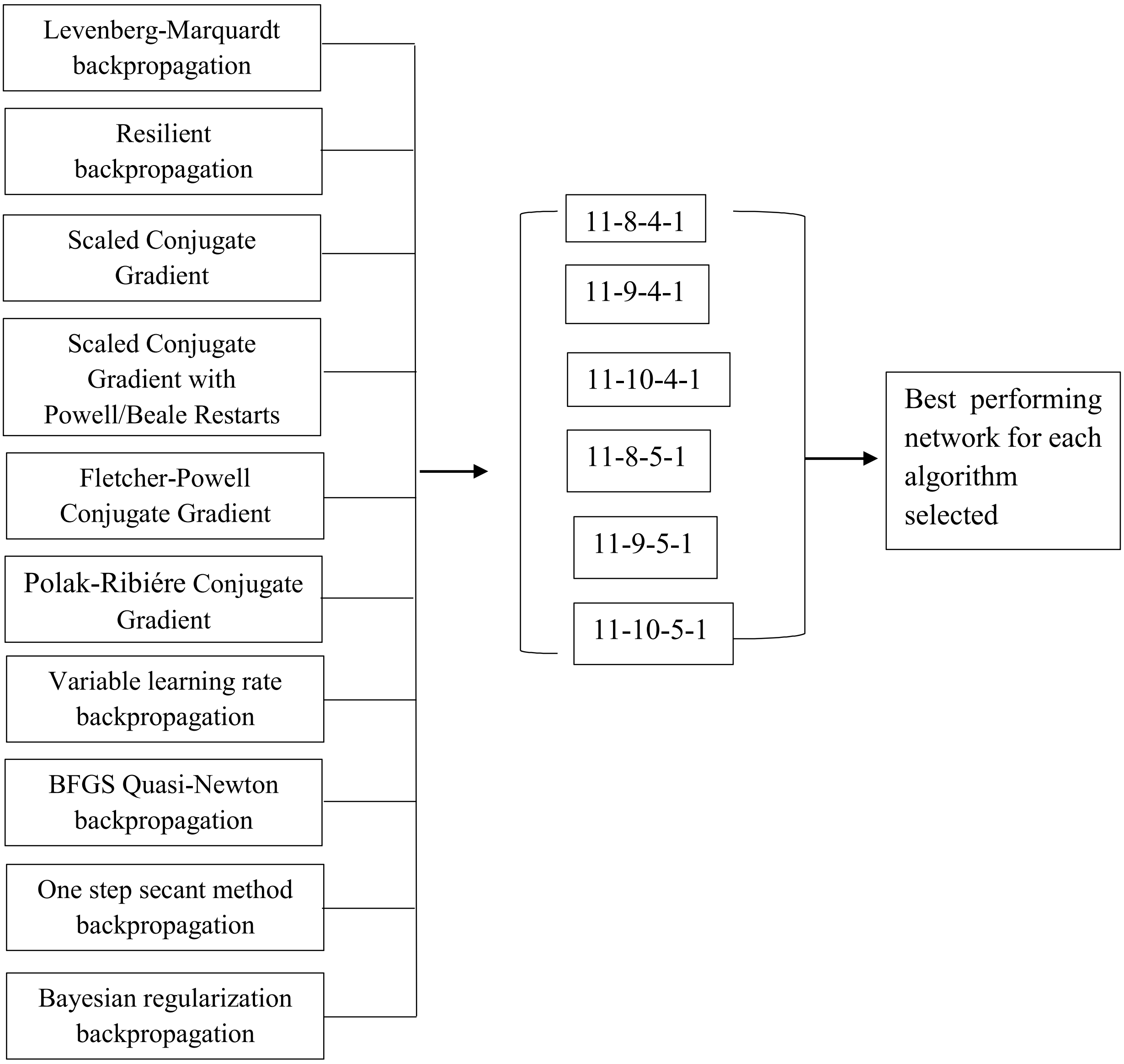


Figure IV-1:Graphic representation of the initial algorithm selection

In this stage the selection of the backpropagation method-algorithm is made. A demonstration of the different algorithms and the different network's architectures tested is given in the Figure IV-1. The networks consist of 11 nodes at the input layer (11 parameters selected as input signal) and 1 node at the output layer, as the value that we want to predict is only one, the shaft power needed for a given set of input signals. At this stage we allow the number of nodes at the hidden layers to vary on a short range. As demonstrated, the nodes at the first hidden layer vary from 8 to 10 and at the second hidden layer from 4 to 5. At this stage all possible combinations of training algorithms and different architectures demonstrated at the Figure

IV-1, were tested. Sets of networks trained with the same training algorithm, but with different architectures were made. Then, a comparison between the best performing networks of each set is done, in order to conclude in the algorithm, which fits best on our problem. The best performing network of each training algorithm set is selected automatically, through an assessment of the generalization characteristics. This evaluation, is based on the network of each set with the maximum regression value and the minimum mean square error, evaluated over the same validation set.

Training Algorithms	**Regression values**	**Slope of Regression**	**Offset of Regression**	**Mean Square Error**
Levenberg-Marquardt backpropagation	8.53E-01	7.59E-01	1.75E-02	5.79E-04
Resilient Backpropagation	8.25E-01	7.04E-01	2.34E-02	6.28E-04
Scaled Conjugate Gradient	6.63E-01	4.51E-01	4.06E-02	1.10E-03
Conjugate Gradient with Powell/Beale Restarts	6.34E-01	4.47E-01	4.59E-02	1.20E-03
Fletcher-Powell Conjugate Gradient	7.46E-01	5.48E-01	3.31E-02	9.09E-04
Polak-Ribiére Conjugate Gradient	6.67E-01	4.29E-01	4.37E-02	1.10E-03
Variable Learning Rate Backpropagation	5.22E-01	2.92E-01	5.35E-02	1.30E-03
BFGS Quasi-Newton Backpropagation	5.85E-01	3.48E-01	4.66E-02	1.40E-03
One Step Secant Method	5.35E-01	3.35E-01	4.65E-02	1.30E-03
Bayesian regularization backpropagation	9.34E-01	8.89E-01	9.30E-03	2.72E-04

Table IV-1 : Training algorithms evaluation

At this table the performance of the best network of each training algorithm is presented. The evaluation is done based on the minimum cost function error (Mean Square Error is selected as the cost function) in addition to the best regression characteristics at the validation set. The regression value describes how the predicted values fit at the targeted diagonal, while the slope describes the deviation of the angle from the diagonal (45 deg or the line $y = x$). Lastly, offset of regression describes the parallel deviation of the fitted line to the $y = x$ target.

The input consists of the 11 parameters selected, described in the previous chapter, while the output is the predicted power. The goal is to have a predicted power as close as possible to the power measured by the torque meter and produce a network that makes predictions close to the diagonal at the full range of power and input parameters.

Regression over the training and test set, for the best performing network of the Table IV-1 is demonstrated below.

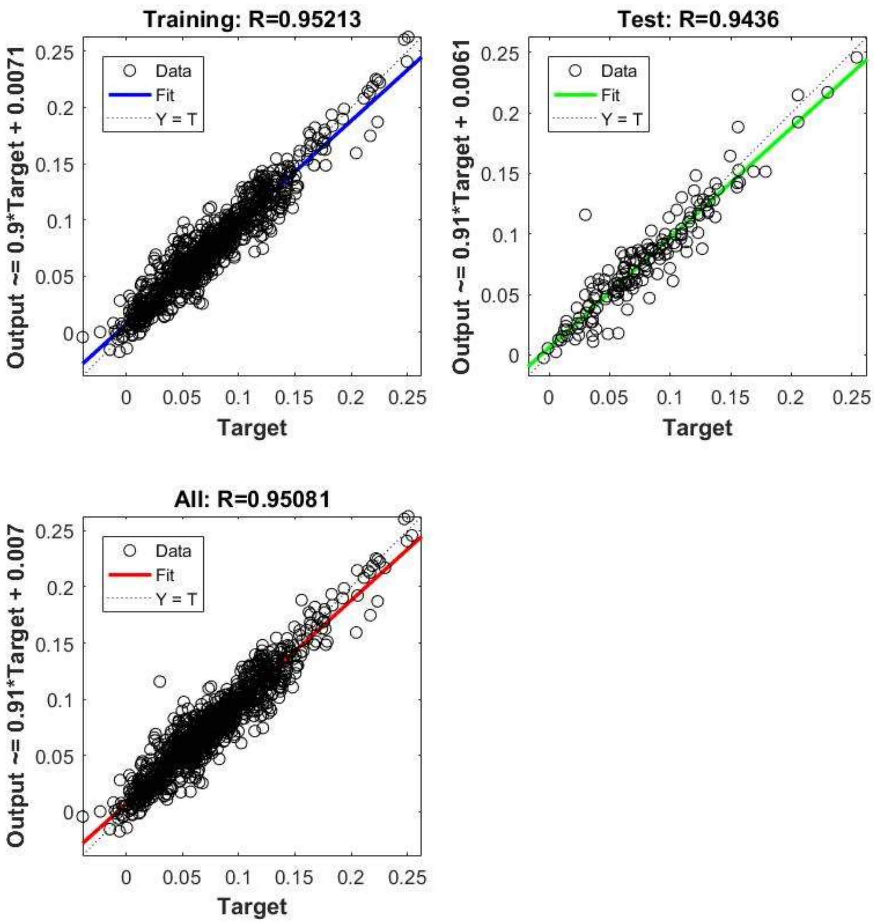


Figure IV-2 : Bayesian regularization backpropagation algorithm regression characteristics over the training and the test set

Regression over the validation set was done externally (after completing the training process) and the Figure IV-3 demonstrates the performance of a neural network, trained with the Bayesian regularization backpropagation algorithm, over a set that was not used for the training, thus it is in a way a demonstration of the generalization properties of the network. For each of the neural networks generated, the corresponding regression values and mean square error were calculated and evaluated at the course of the selection of well performing networks. Mean square error as demonstrated, represents the difference between the output values of the neural network and the targeted (measured) values. On the other hand, the regression value is an indicator of the relationship between the target outputs and the network's outputs. The regression value ranges between one and zero, where one corresponds to an exact linear relationship ($y = x$) between output and target values and zero to a non-fitting scatter.

R represents the proportion of variation in the response value compared to the target. It is defined as: $R^2 = 1 - \frac{SSE}{SST}$, where SSE is the sum of squared errors given by the equation $SSE = \sum_i^n (y_i - t_i)^2$ and SST is the sum of squared values.

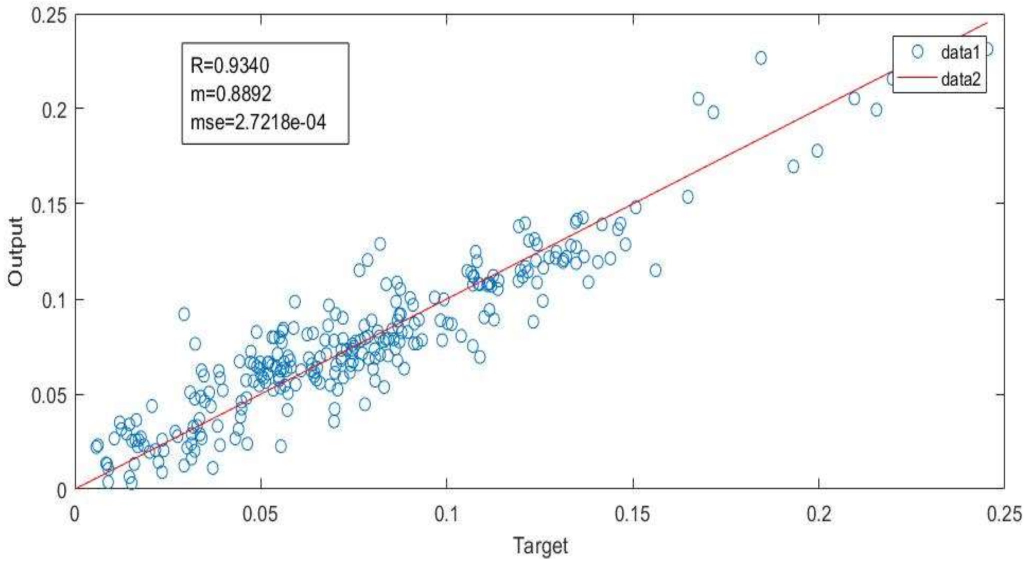


Figure IV-3: Bayesian regularization backpropagation algorithm Regression characteristics over the validation set

Where, data1 is the output of the trained network (prediction) and data2 is the measured values for the specific data set.

A. Improving Neural Network's Generalization and Avoiding Overfitting

The main problem that occurs during neural network training is overfitting. Addressing this problem, we focused on the generalization properties of different neural networks. Networks memorize the training examples, but the issue is their ability to generalize to new situations. Using Bayesian regularization backpropagation algorithm to train them, improved significantly the performance of the network's addressing this matter. One method for improving network generalization is to use a network that is just large enough to provide an adequate fit. The larger network used, the more complex the functions the network can create. If a small enough network is used, it will not have enough power to over fit the data. However, identifying the network's architecture that is large enough to address the problem, while it is not too large to over fit is a complex task. An attempt to address this issue was done by (Hagan M. H., 1996). Unfortunately, it is very difficult to know beforehand how large a network should be for a specific application. To demonstrate this, a network was trained with the Bayesian regularization backpropagation algorithm, but with a significantly large number of neurons per layer. The computation time required was greater than the time needed to train "ordinary" networks, about 10-15 x time compared with Levenberg - Marquardt backpropagation algorithm. Networks architecture is presented in the Figure IV-4.

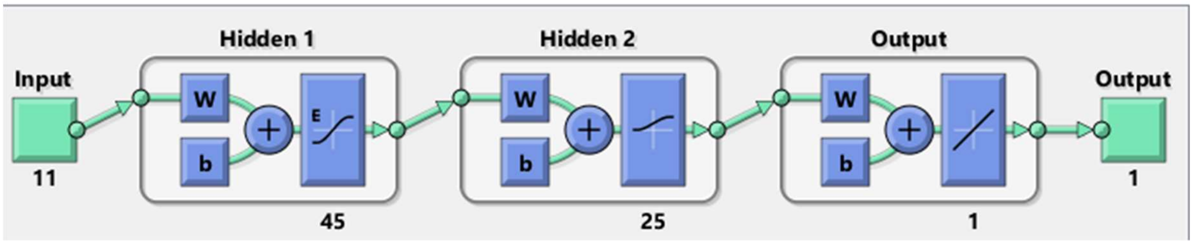


Figure IV-4: Neural Network Architecture (overfitting demonstration)

The above network, consists of two layers, with 45 and 25 neurons respectively. The input and the output parameters as well as the training and validation set, are the same as the one used for all previous networks. The transfer functions selected are: Elliot sigmoid from the first hidden layer to the second, log sigmoid from the second hidden layer to the output layer and a linear function to connect the output layer to the final output.

As expected the neural network started to "memorize" the data and produced a very accurate prediction over the set of data it was trained with. The error on the training set is almost zero.

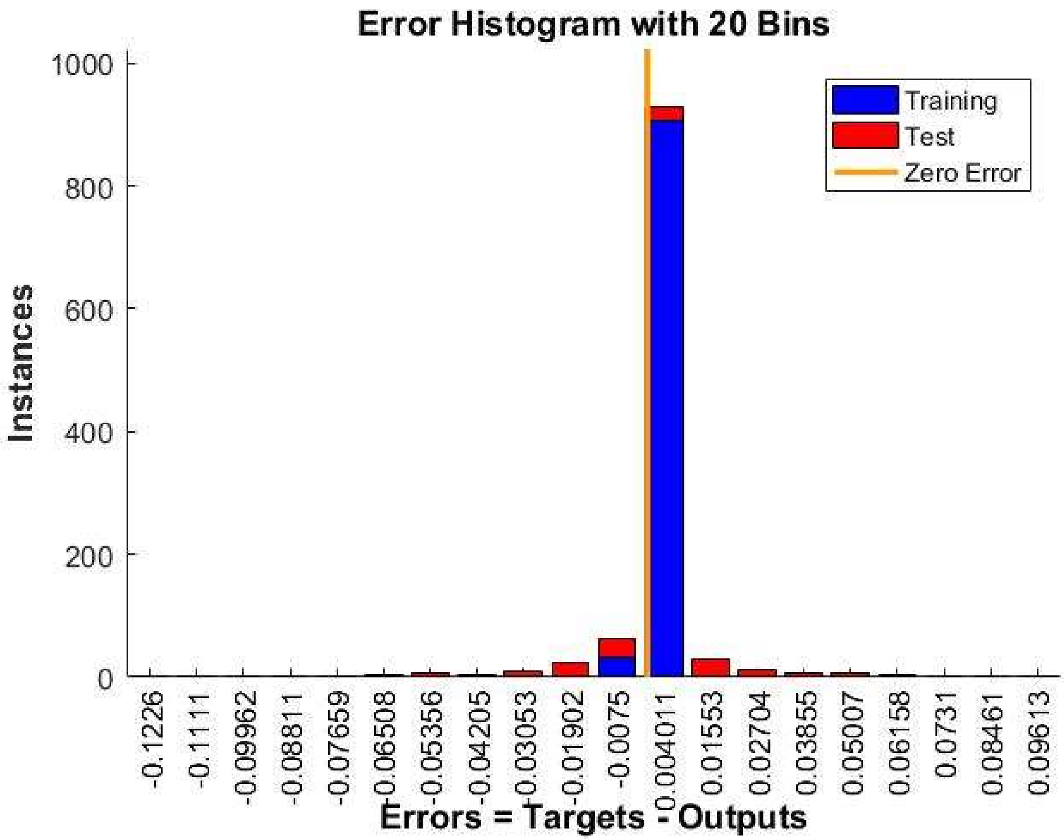


Figure IV-5: Error at the training set(overfitting demonstration)

However, for the validation and the test set the results were not so good. An overview can be seen at the following graphs.

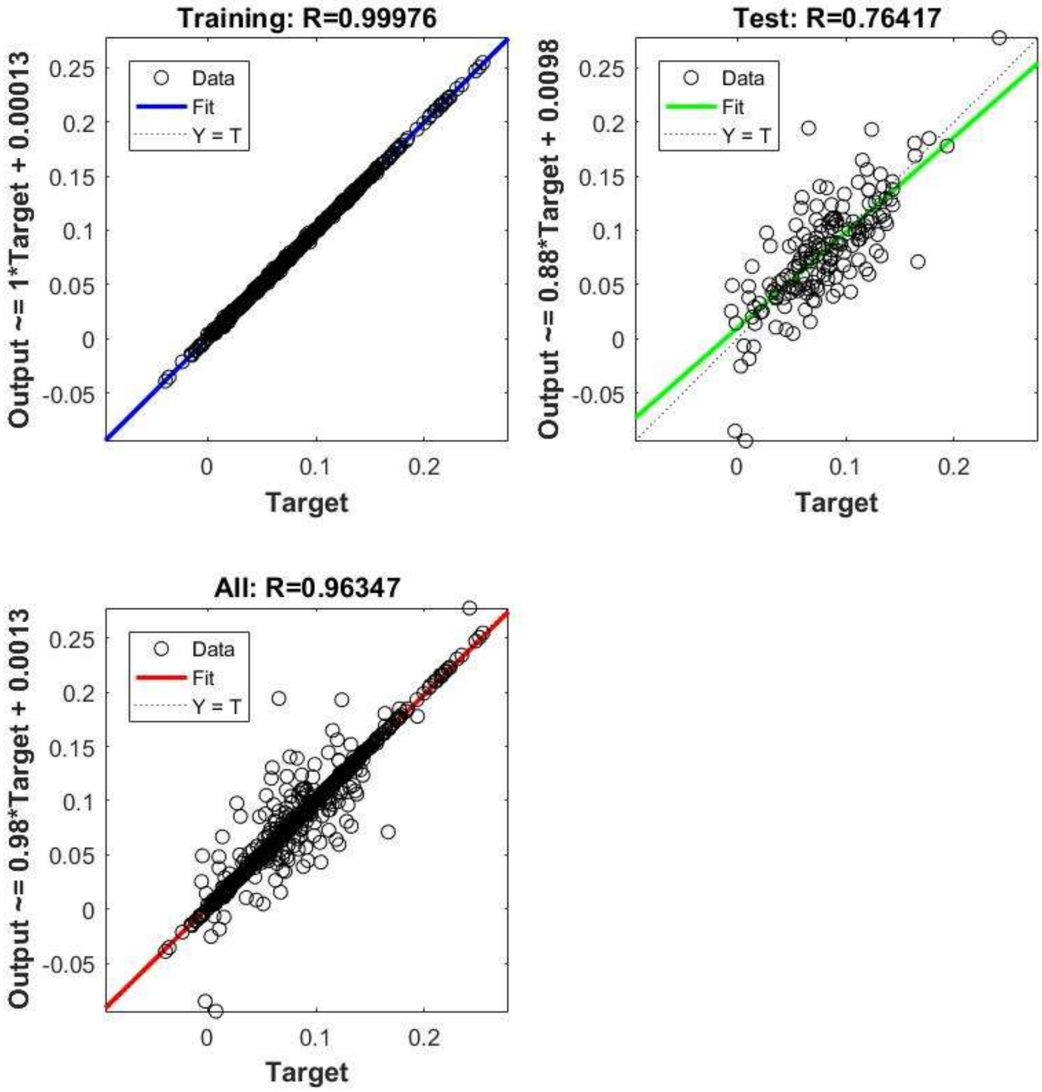


Figure IV-6: Regression (overfitting demonstration)

Regression at the trained data is almost perfect. On the other hand, at the test set, the network is not performing well.

At the validation set, regression characteristics are $r= 0.7150$, $m=0.8415$ and $b=0.0107$. Where, r is the regression value, m is the slope of regression and b is the offset of regression. Mean square error over the validation set was calculated to be $mse=0.006$, which is above the range of the other networks trained with the Bayesian regularization algorithm.

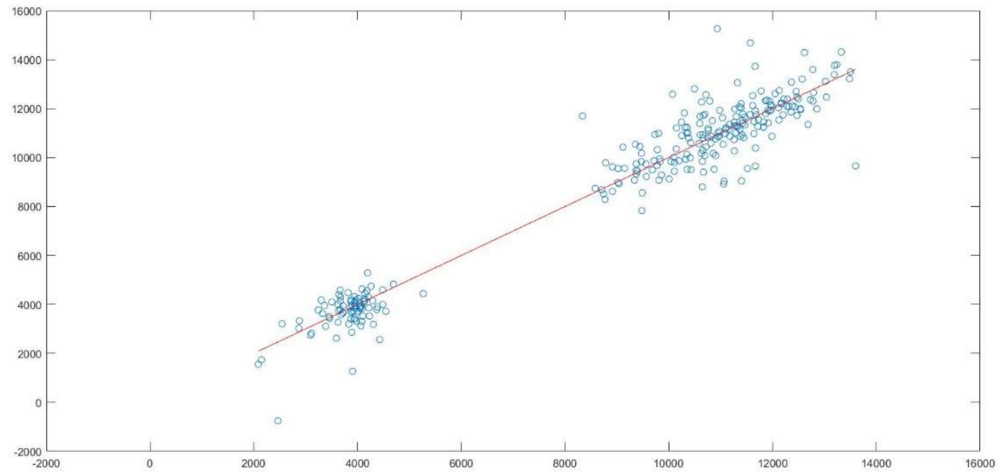


Figure IV-7: Regression over the validation set (overfitting demonstration)

A simpler way to improve generalization, which will be addressed later in this study, especially when caused by noisy data or a small dataset, as in our case (2085x11 input data set matrix), is to train multiple neural networks and average or weight their outputs. To demonstrate this, the mean square error of their average output is compared to the lowest mean square error of the networks trained in each case. This is especially helpful for a small, noisy dataset, especially, in conjunction with the Bayesian Regularization training algorithm. This approach is described by (Dan Cireşan, 2012) in the framework of a classification problem. As stated, averaging the outputs generalizes just as well or even better on the unseen test set or on a validation set.

B. Implementation of Bayesian regularization backpropagation algorithm

At this paragraph different networks are presented. Bayesian Regularization training algorithm was used for training, as the performance of the networks trained with this algorithm is significantly better than any other algorithm tested at this given problem. The networks developed, consist of two hidden layers with a variable number of neuron in each. Neurons at the first layer vary from 5 to 20, as the second layer consists of 2 up to 10 neurons. The number of the neurons located at each layer was decided, based on two main reasons. Firstly, more complex networks require significantly more computational power and secondly, the effect of overfitting in more complex networks (as the one demonstrated) is significant. Different transfer functions were tested in order to rank them and select the most suitable architecture. As described above, the method chosen to rank them was the mean square error of the average of their output. The validity of this decision will be clear after the further investigation which will be demonstrated at a following stage.
A summary with the mean square error of the average output of the different set of networks (with varying transfer functions) is presented in the Table IV-2.

	Activation function (2nd Layer)				
Activation function (1st Layer)	**Transfer function**	Elliot sigmoid	Log sigmoid	Linear	Tan sigmoid
	Elliot sigmoid	1.42E-04	1.42E-04	1.63E-04	1.40E-04
	Log sigmoid	1.77E-04	1.43E-04	1.77E-04	1.46E-04
	Linear	1.66E-04	1.59E-04	8.56E-04	1.64E-04
	Tan sigmoid	1.44E-04	1.46E-04	1.75E-04	1.55E-04

Table IV-2 : MSE of the average output of networks with different activation functions

To demonstrate the improvement of the prediction by the use of the average of outputs, we will focus on the best set of networks in terms of mean square error of the above table. The minimum mean square error can be observed at the set of networks, using the Elliot sigmoid transfer function to activate the second hidden layer and the Tan sigmoid function to activate the output layer, as shown at the networks' representation graph below.

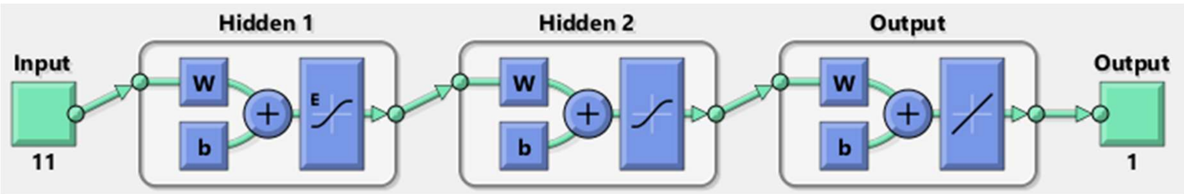


Figure IV-8 : Set of Neural Networks Architecture(Elliot sigmoid – tan sigmoid)

As expected the mean square error over the training set is decreasing as the complexity of the network is increasing.

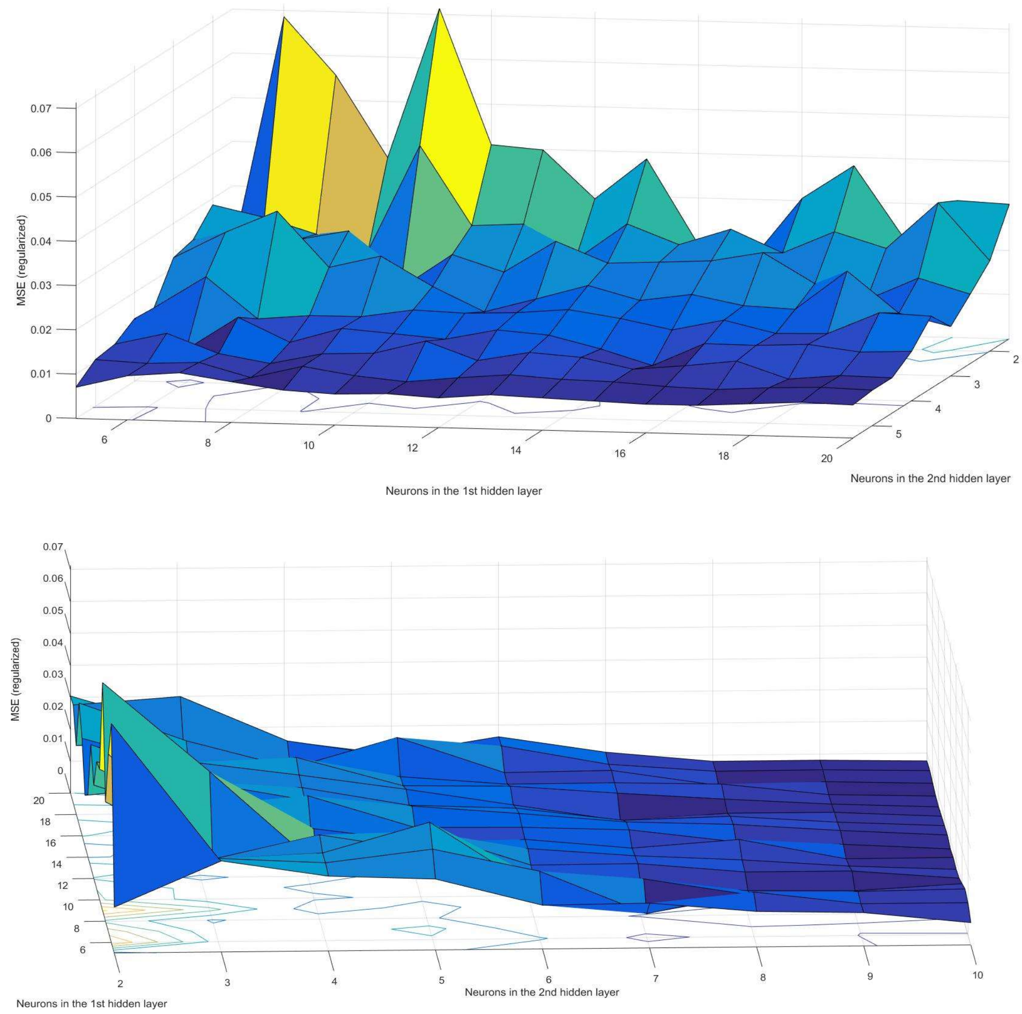
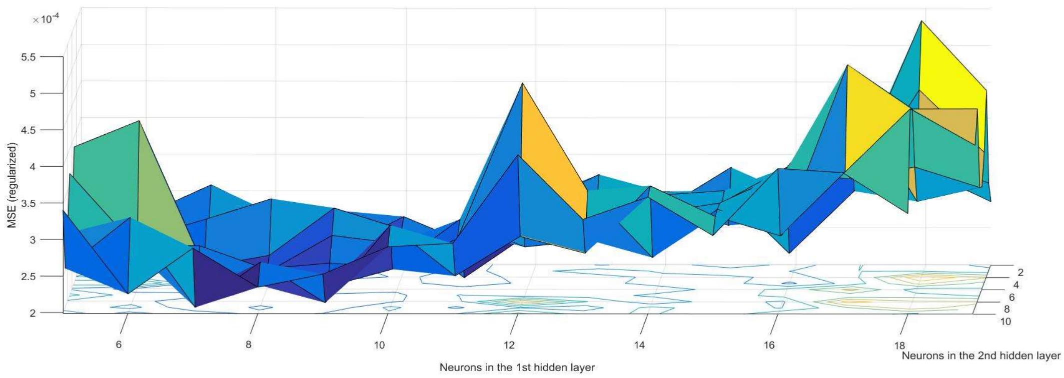


Figure IV-9: Mean Square error (regularized) over the training set (Elliot sigmoid – Tan sigmoid)

However, when calculating the same error over the validation set, the outcome is different.



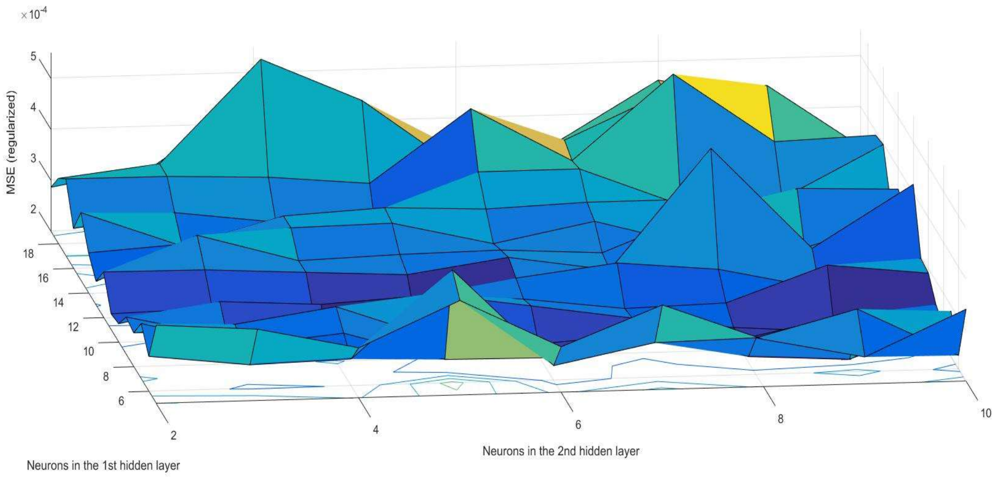


Figure IV-10: Mean Square error over the validation set (Elliot sigmoid – Tan sigmoid)

At the above graphs, the effect of overfitting is demonstrated. For more complex networks the prediction of the network for data that were not used for training, is poor. The same can be observed also from the R values.

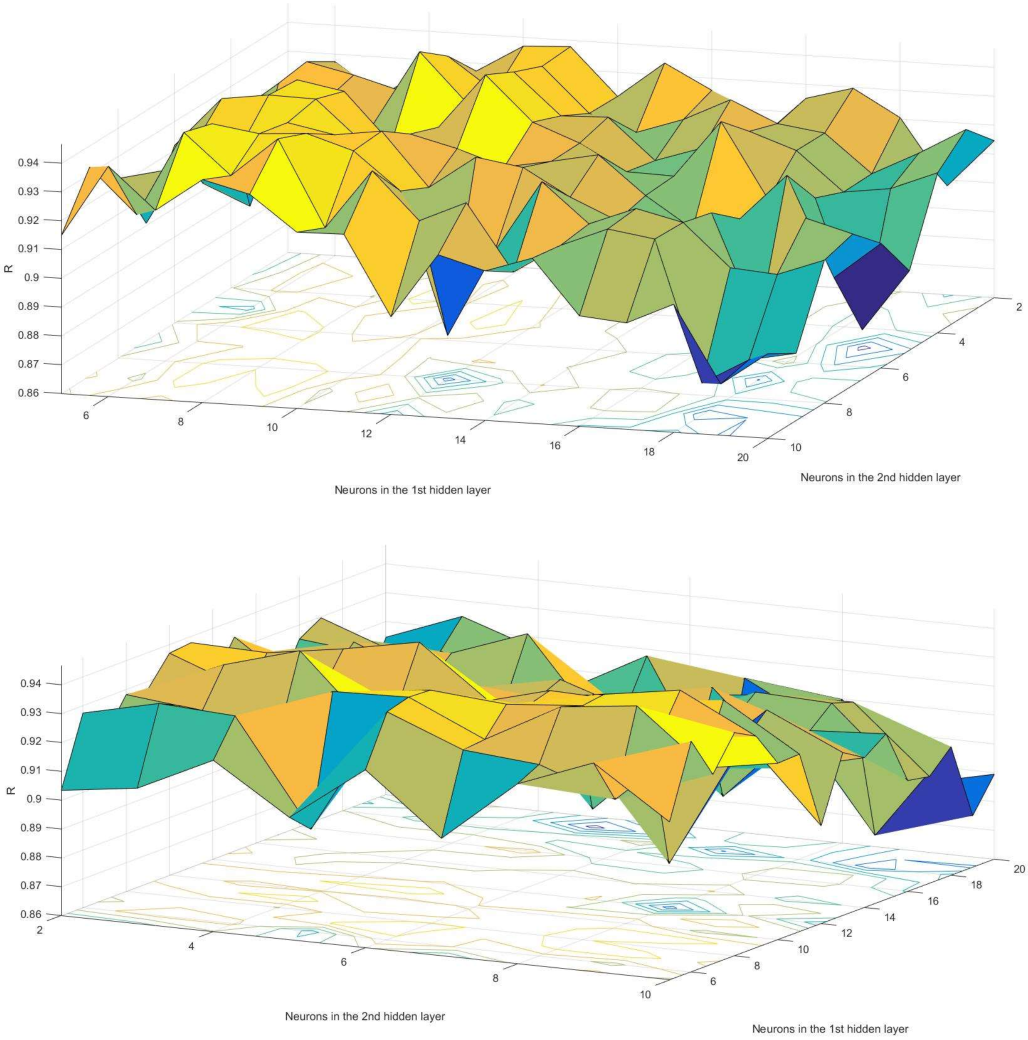


Figure IV-11: Regression value over the validation set (Elliot sigmoid – Tan sigmoid)

From the set of neural networks developed with Elliot sigmoid and tan sigmoid as activation function for the first and the second hidden layer respectively, the best generalization characteristics (least mean square error and maximum R) is accomplished by the network consisting of 8 neurons at the first layer and 9 neurons at the second hidden layer. The evaluation of the generalization characteristics is done by calculating the mean square error and the regression over the validation set.

$MSE = 1.99e - 04$, $R = 0.947$.

On the other hand, when averaging the output of all networks included in the set, the outcome is:

$MSE = 1.63e - 04$, $R = 0.996$.

By selecting the best preforming networks of the set and averaging, the result improved further.

$MSE = 1.35e - 04$, $R = 0.997$.

The criteria applied for the selection of the best performing networks are the following:

- Mean Square Error, on the validation set, of each individual network to be less than $4.00e-04$
- While regression value, on the validation set, (of each individual network) to be greater than 0.94.

An interesting observation based on this set of neural networks is that while each independent network contains noise characteristics, the prediction of the average output of the Elliot Sigmoid & Tan Sigmoid set of networks is one of the best tested. This could possibly be attributed to the random error effect, which is decreased when averaging a number of networks' output.

Following the same analysis, the results of the second best performing neural network set is presented below. The activation functions used are the Elliot sigmoid and Log sigmoid functions respectively.

The results over the training set are similar.

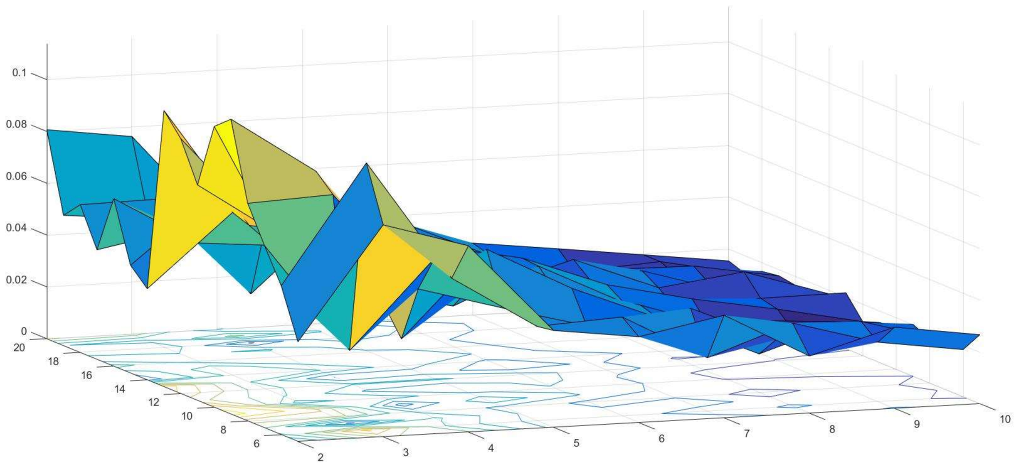


Figure IV-12: Mean Square error (regularized) over the training set (Elliot sigmoid – Log sigmoid)

Mean square error over the validation set is presented in Figure IV-13.

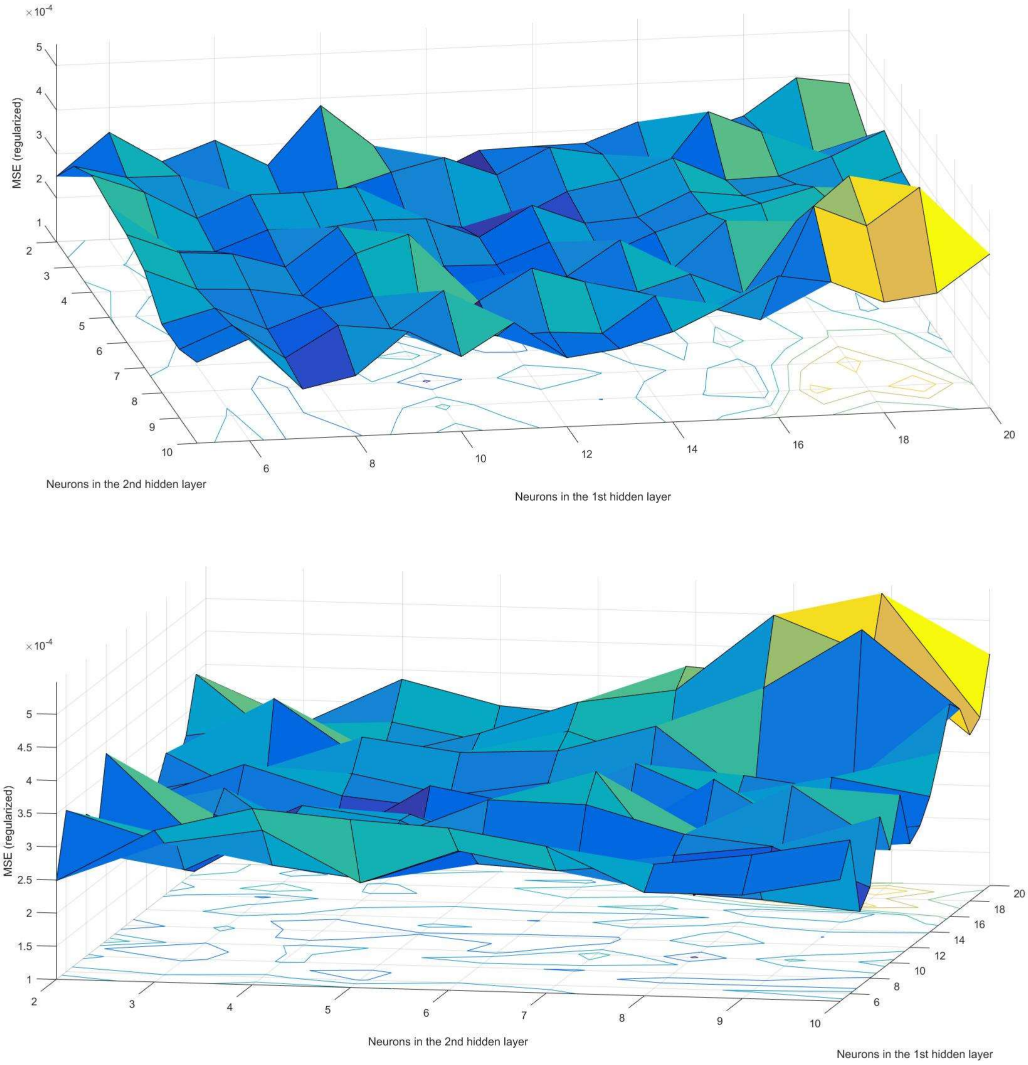
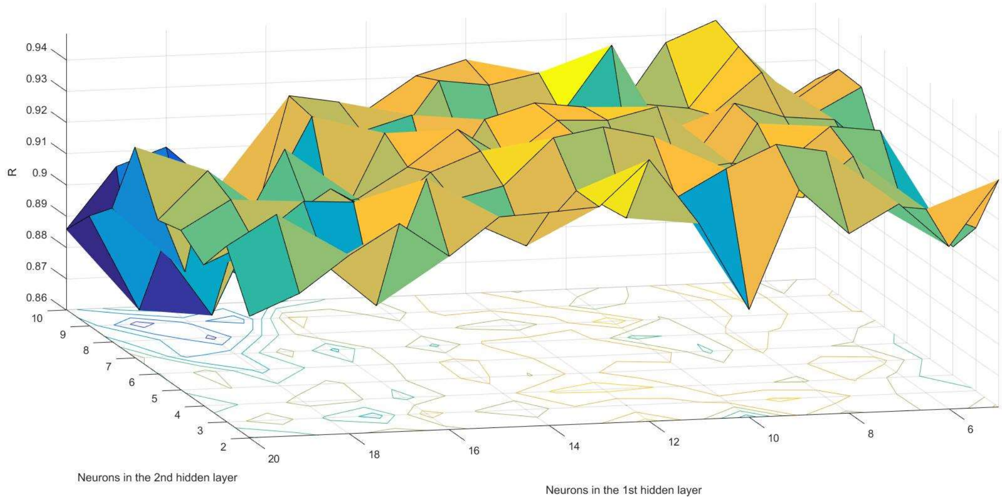


Figure IV-13: Mean Square error over the validation set (Elliot sigmoid – Log sigmoid)

Regression values:



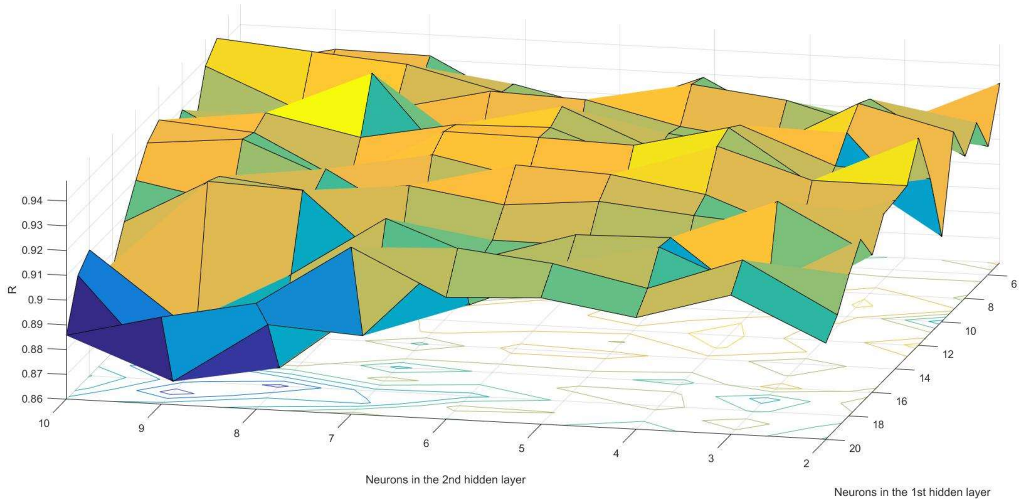


Figure IV-14: Regression value over the validation set (Elliot sigmoid – Log sigmoid)

Best performing single neural network:

$MSE = 1.93e - 04$, $R = 0.948$.

Averaging the output of all networks included in the set,

$MSE = 1.60e - 04$, $R = 0.996$.

Selected networks of the set, following the criteria described previously,

$MSE = 1.33e - 04$, $R = 0.997$.

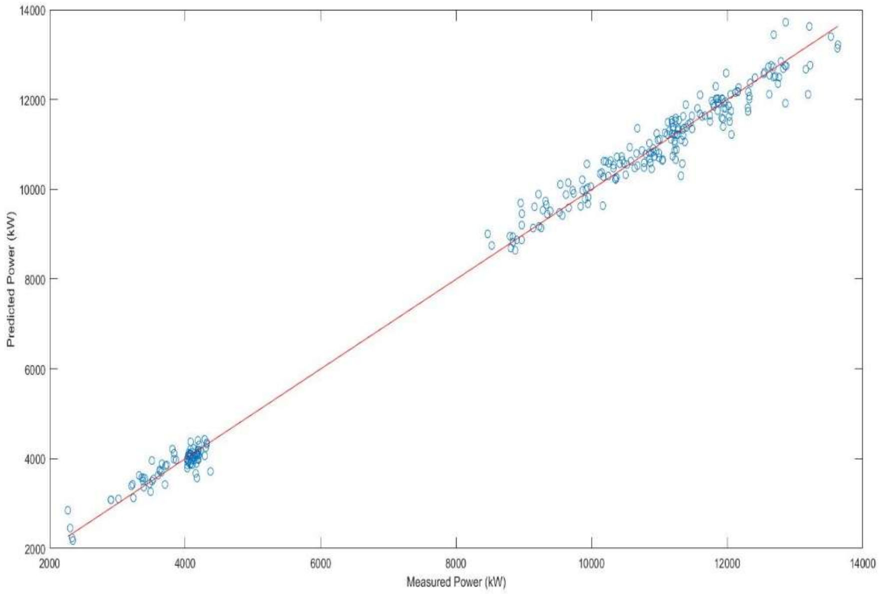


Figure IV-15 Predicted versus Measured power (validation set)

At the above graph the prediction of the set of selected neural networks versus the measured power by the torque meter are plotted.

V. Application- Fouling Identification

Firstly, to demonstrate the accuracy of the system, a graph with the time history of the measured power versus the prediction, over the initial data imported (training, test and validation) is presented in Figure V-1, as well as a graph of the regression over the **validation** set in Figure V-2. The prediction is done through **averaging the output of selected networks**, with different architectures, selected based on their performance over the validation set, following the criteria described at the previous chapter. The network set, from which the best performing networks were selected, consists of 308 different networks, all trained with the Bayesian Regularization Backpropagation algorithm, designed with an Elliot sigmoid activation function at the first hidden layer and a Log sigmoid activation function at the second hidden layer. Networks differ at the number of nodes assigned to each hidden layer. At the first hidden layer the number of nodes vary in the range of 4 to 25, while at the second layer they vary from 2 to 15. All possible combinations were tested. The resulting set of selected networks is not defined, as the selection is done through complying with the criteria applied. The criteria, as described previously, are the following. Firstly, the Mean Square Error of each individual networks at the validation set should be less than 4.00e-04, while regression value, on the validation set, (of each individual network) must be greater than 0.94.

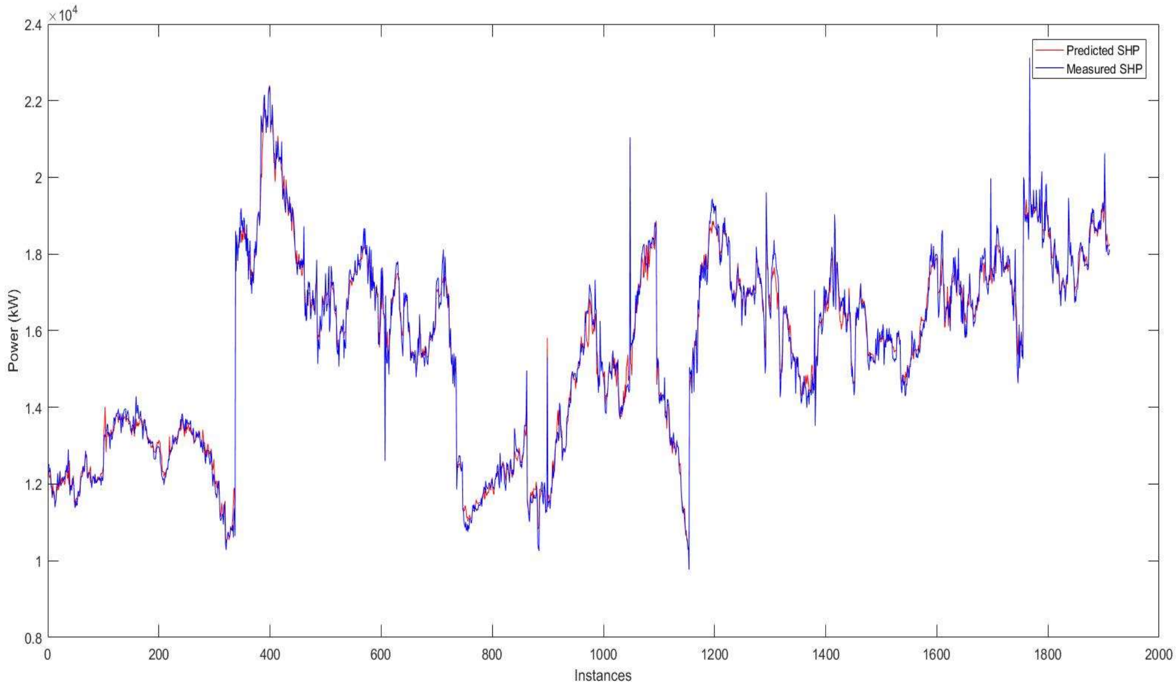


Figure V-1: Predicted versus Measured power (data history used for modelling)

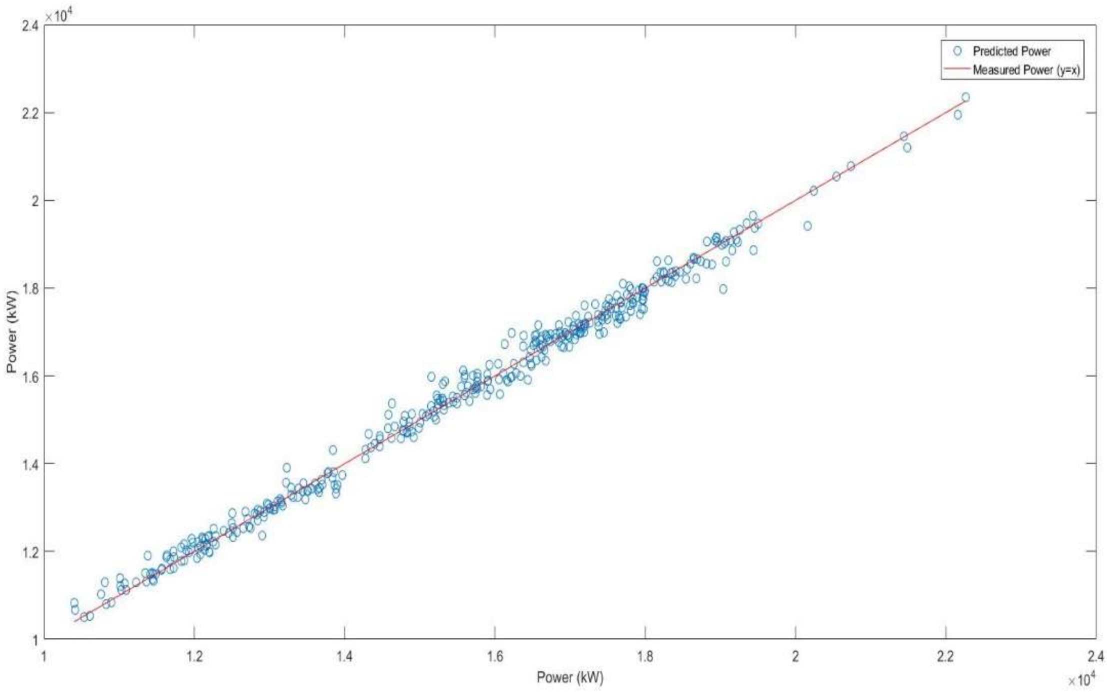


Figure V-2: Predicted versus Measured power Regression (validation data)

Regularized Mean Square Error, as presented at the previous chapters, for the current set of networks is: $8.7357e - 05$, and the regression value is $R = 0.996$. The Mean Square error after restoring the output to the original units (kW) is $MSE = 5.4598e + 04$ (normalization is necessary for training and processing of data and if the developer do not define the method, every algorithm has its default normalization process). It is useful to note that the subject vessel has an engine with a Maximum Continuous Rating (MCR) of 25,330 kW and the normal operating load is between 8,000 - 18,000 kW.

Following is the error histogram of the validation set (error unit in kW):

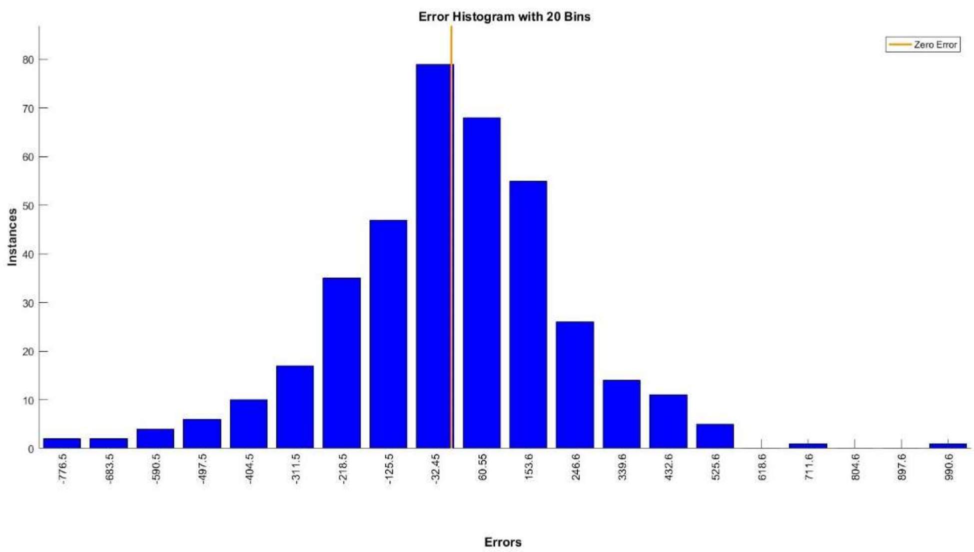


Figure V-3: Error Histogram (validation data)

To evaluate their potential use, the models were tested at two vessels of the same class (VLCCs with the same hull) managed by Maran Tankers Management Inc.

Firstly, the resulting model was used to evaluate the performance of vessel A (vessel used for developing the model) and its current condition. A random laden leg of 10 days' duration has selected. This leg was made, approximately 2 years after the delivery. The evaluation is in line with the results of the underwater inspection(s), where no significant fouling has been observed (less than 5% of the vertical sides' area, covered with light slime).

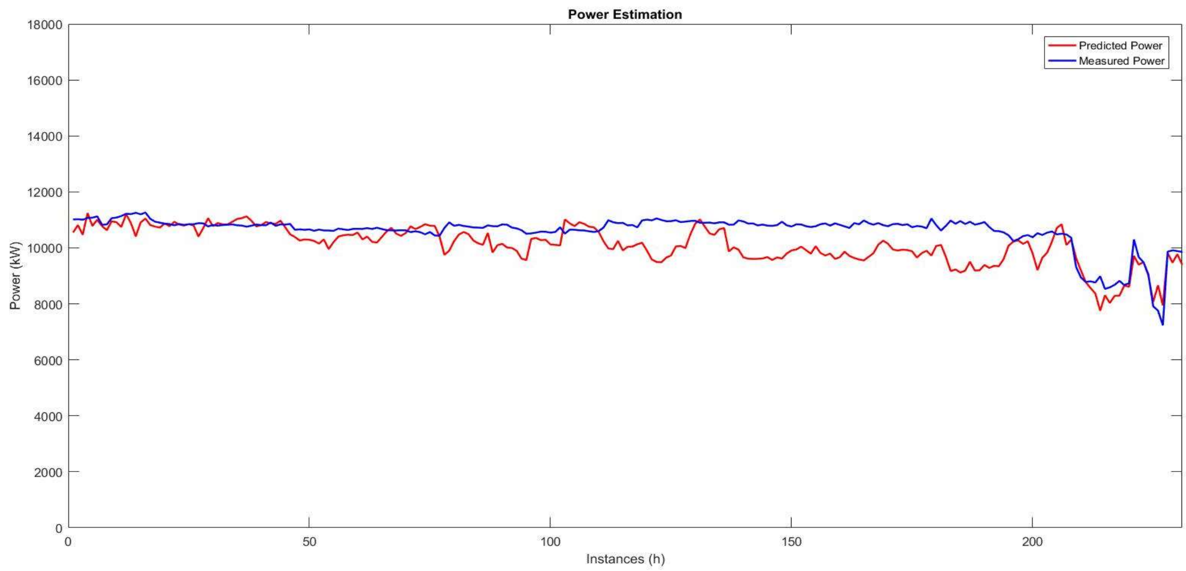


Figure V-4: Power estimation compared with the measured shaft power - Performance evaluation

As demonstrated at the graph above, the deviation of the predicted power compared with the power measured by the torque meter is minor. Below a graph with a set of indicative parameters is presented to describe the conditions in which the vessel was sailing.

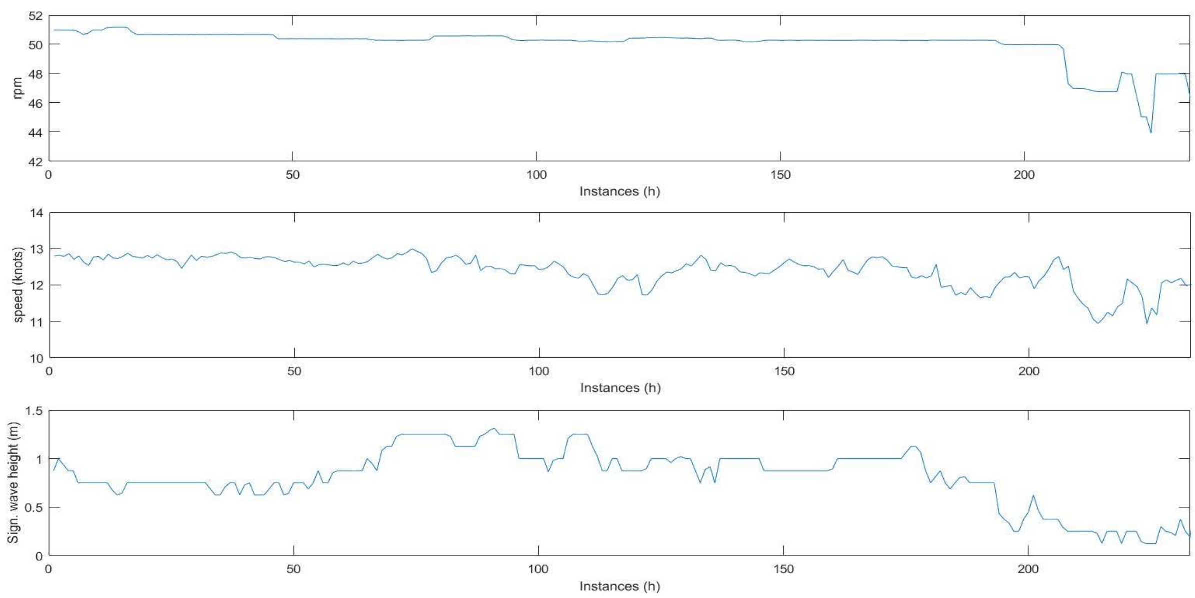


Figure V-5: Input parameters – Performance evaluation

It can be observed that the prediction is correlated strongly with the speed, thus, the deviation of speed as an input parameter creates a deviation at the prediction value.

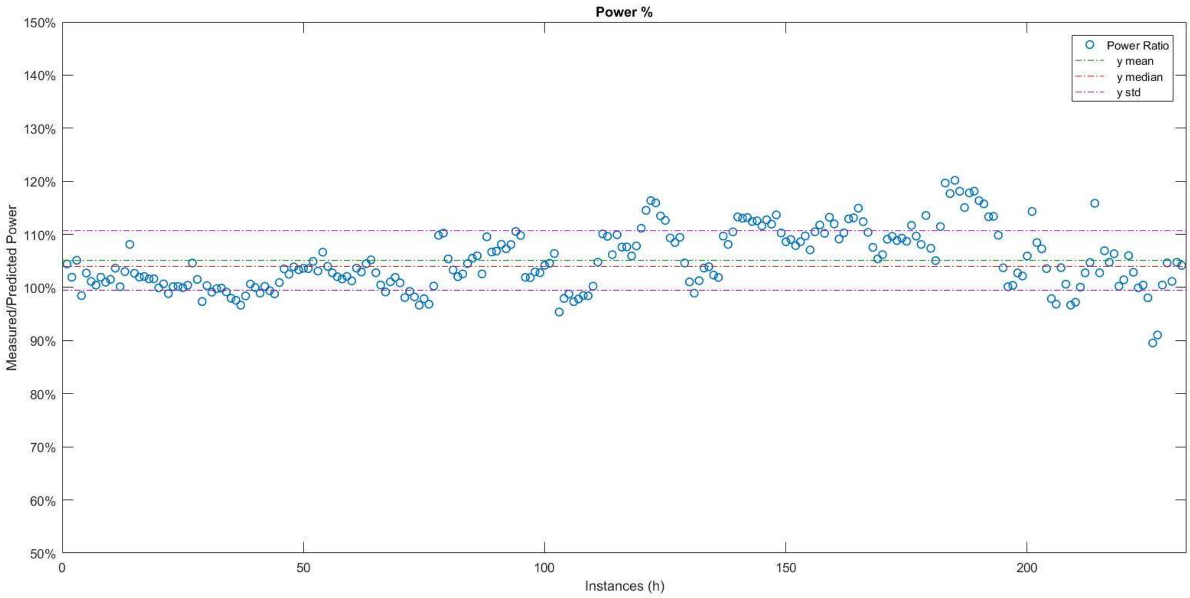


Figure V-6: Power% - Performance evaluation

At the period of evaluation, the vessel performed at average 5% worse than the model, as shown above, with a median value of 4.2%. Values in this range are expected and treated as normal due to the degradation of the hull and propeller performance.

Another demonstration of the use of the developed system is given on a sister VLCC, vessel B, with the same hull and equipment as the one used for this study. When the hull and propeller are clean, the vessel performs according to the model.

Vessel B was inspected and found relatively clean, approximately 2 months prior sailing to a high fouling risk area. Unfortunately, the vessel remained idle waiting to load for 3 weeks. After sailing, an increase in the power needed to propel the vessel was observed. The predicted power for the given operational and environmental conditions, compared to the real time shaft power measured by the torque meter is presented in the Figure V-7.

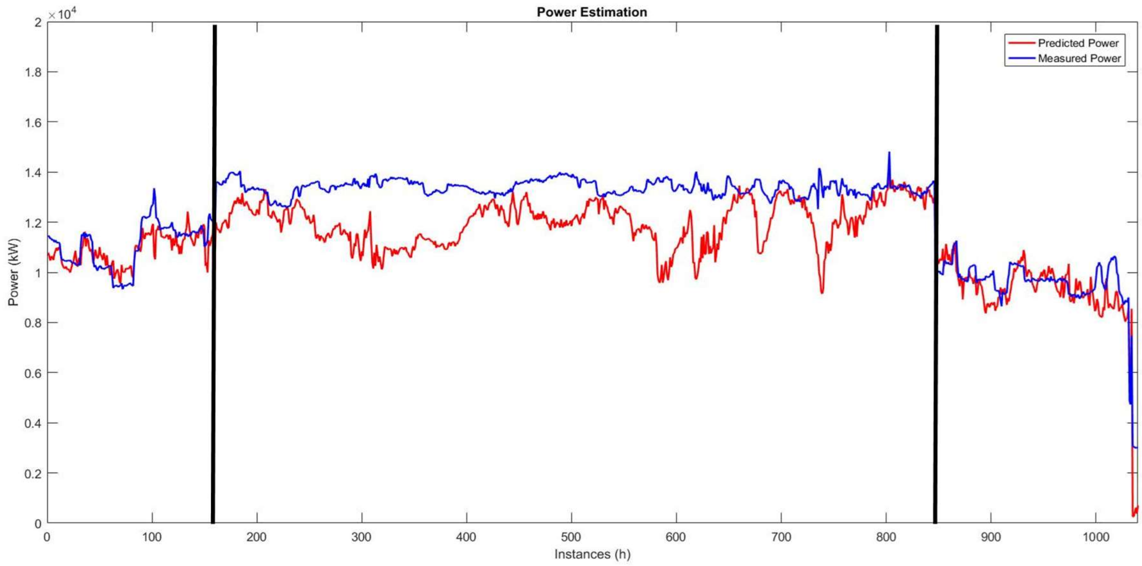


Figure V-7 : Demonstration of fouling identification – Performance evaluation

At the above graph, the first vertical black lines represent the end of the first sea passage, before idling, followed by the leg after idling, where, the last part, after the second black vertical line, corresponds to the leg after cleaning.

Taking into account this evaluation, an off-schedule inspection was arranged and the vessel was found fouled (fully covered) up to the ballast waterline with moderate to heavy fouling (heavy slime-grass) and the company's decision was to take action. After hull cleaning and propeller polishing the vessel managed to sail according to the model (third part of the above graph). This evaluation, demonstrates a useful implementation of machine learning and its benefits as well as the promising aspects of these kind of technologies.

The data used for this comparison are almost unfiltered and without any pre-processing. As a result, the parameters of the input vector are noisier than the data set used for training. Calibration of the instruments is also an issue, as it differs between the two vessels. The time series of the indicative parameters of the external conditions are presented in Figure V-8.

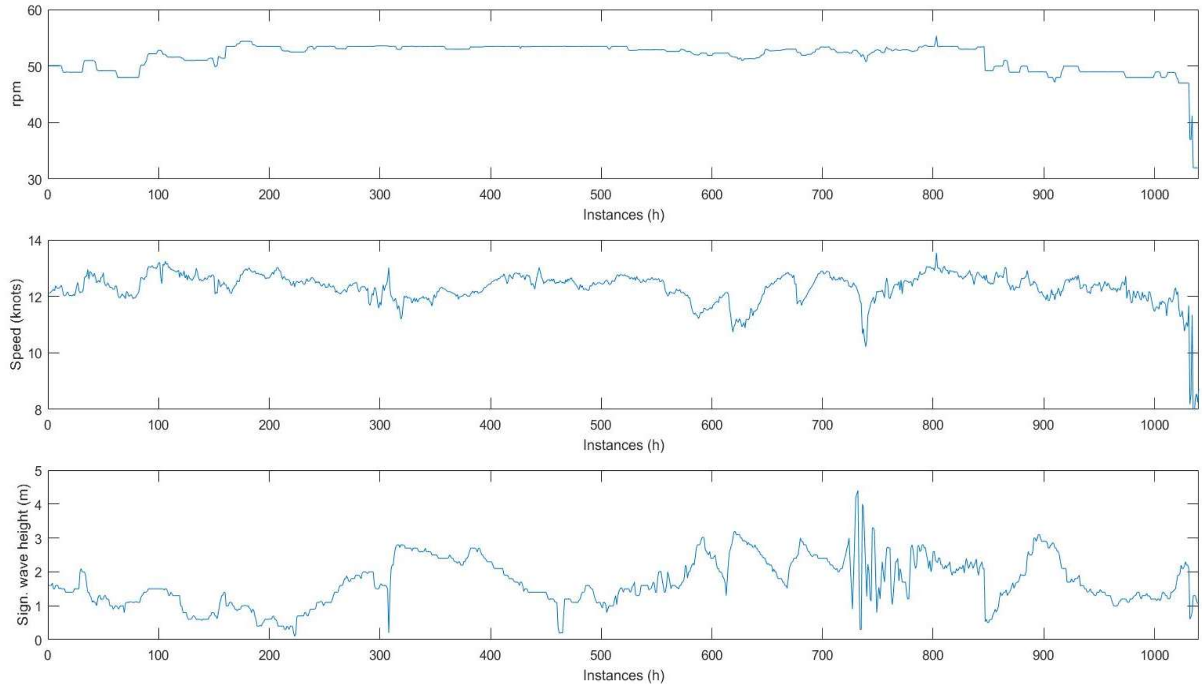


Figure V-8: Demonstration of fouling identification - Input parameters – Performance evaluation

Unfortunately, the unexpected high speed - signal fluctuation, induce an error and a similar fluctuation at the predicted power. However, the impact of fouling is significant and easy to observe. A method to increase reliability and to tackle the issue of fluctuating signals of key parameters, in our case the speed through water signal, is addressed in studies made by (Lajic, 2018) and (Hansen, Blanke, & Adrian, 2010).

VI. Conclusion and Recommendations

The purpose of this work was to investigate, and develop a performance module for the prediction of the shaft power needed to propel the vessel at any given external conditions, when assuming clean hull and clean propeller condition. This study is based on auto logged data of a VLCC. The data for the training, test and validation of the networks' accuracy, were obtained by the sensors on-board the vessel and weather data provided by weather data providers. The acquired dataset used for the design and development of the network was carefully selected in order to reassure that all sensors were fully functional, the vessel was under normal operational conditions representing accurately its operational profile and that the condition of its hull and propeller was good. The input vector of the MLPs consist of the following parameters:

1. Speed through water (log) Doppler – Echo Sounder
2. Rudder indicator
3. Wind anemometer relative wind speed
4. Wind anemometer relative direction
5. Average draft (starboard and port) at amid ship
6. Trim
7. List
8. Significant wave weight
9. Swell significant wave weight
10. Swell direction
11. Swell period

A pre-processing of the data was done prior receiving the data sets used for developing the model. The purpose of pre-processing is to remove outliers of the sensors raw (high frequency) readings. Filters have been determined to establish cases where the vessel was sailing at steady state conditions, avoiding transient loads.

Multi-layer perceptrons were trained and evaluated in three stages of trials. In the first stage, the activation functions were held constant and the network's neurons composition and arrangement was free to vary on a limited range. An investigation was made, to decide the training algorithms that fit best to the given problem. After concluding to the most probable, best performing algorithms, we proceed to the second stage, where, the network's neurons composition and arrangement was tested on a bigger range of alternatives and all possible different sets of activation functions were tested. This process resulted in the determination of the network with the best prediction capabilities. The third stage was the evaluation of a different method, where the final prediction was not extracted from a single network but it was computed as the average output of a number of well preforming networks.

The resulting system, consisting of a varying number of networks proved efficient in predicting the power needed to propel the vessel. The generalization properties of this approach were significantly better.

The conclusion drawn by the current work, is that an approach to a complex and non-linear regression problem, such as the estimation of the vessel's shaft power, is feasible via the use of Artificial Neural Networks, when modelled appropriately.

The modelling in this thesis, was in principle done via a selection of parameters related to the physical problems in question. However, correlation between variables can be observed. Limiting the correlation between the input parameters can improve the prediction capabilities and reduce the risk of an oversensitive network. Data validation and data fusion is an aspect that would improve such implementations as the same information could be acquired through a combination of a different set of sources and sensors of varying accuracy. An in deep research of this scope would possibly result in a better performing system. The correlation between variables, in this case, was visualized by principal components analysis of the input matrix. An alternative and most likely more accurate approach to model added wave resistance and the corresponding power could be determined by measuring vessel's responses. Inserting as input parameters, the readings of motion sensors (accelerometers) if available, instead of (or additionally to) weather data provided by third parties would increase the frequency of the input and would describe in a better way the sailing condition of the vessel. However, installing such equipment of sufficient accuracy and maintaining it properly, is rarely found in merchant shipping. Also, developing different modules for the different loading conditions (ballast-laden) may improve the accuracy of the resulting system. Approaches with different machine learning techniques are also applicable and promising. Radial basis function networks, support vector machines, principal components analysis and self-organizing maps, are the most promising among the big range of machine learning tools and methodologies. A method to increase reliability of the performance system and to tackle the issue of fluctuating signals of key parameters is addressed by (Lajic, 2018) and (Hansen, Blanke, & Adrian, 2010).

Machine learning can be also used to approximate the effect of other phenomena, when detailed studies are not available. Estimating the effect of trim over a range of speeds and drafts can be investigated if the required data to address the problem are available. A number of other mapping or regression problems could be investigated through the scope of Artificial Neural Networks, given the required tools and data to address them. Overall, applications based on machine learning, given the amount of data available, are feasible and promising solutions.

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